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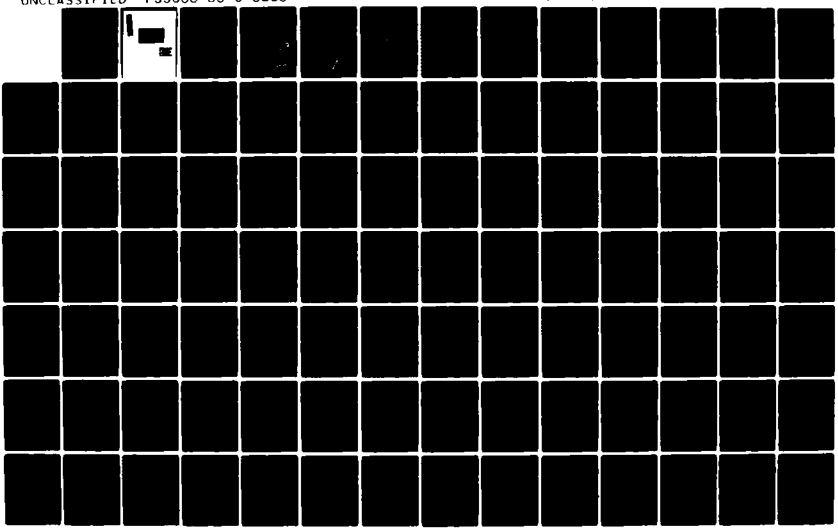

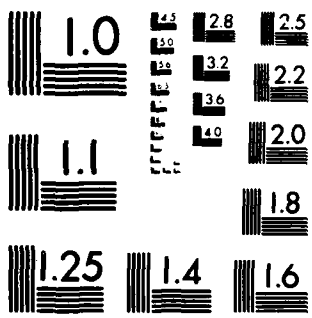

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An Evaluation of Alternate D062 Inventory Management Policies When Leadtimes are Random

by

W. Steven Demmy

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Section I

Introduction

Overview

Three of the major assumptions that are embedded in the current reorder level computations utilized in the Economic Order Quantity (EOQ) Buy Computation System (D062) are the following:

1. Demand in a lead time is normally distributed.

2. The leadtime is known and constant.

3. The mean and standard deviation of leadtime demand may be accurately estimated from available history.

These assumptions are used in a number of commercial inventory management systems, and simulation studies using actual demand history for Air Force items have shown that the resulting formulas are significantly more cost effective than the inventory level computations which were previously in use. However, several recent studies have shown that the above assumptions may not

be an accurate approximation to the characteristics of a number of D062 items. For example, Hayya (1980) observed that leadtimes for a sample of 62 high activity D062 items had significant variability. Also, in Reference 3 it was found that the distribution of errors in forecasting demand in a given leadtime is better described by a combination of exponential functions than by a normal distribution.

If assumptions one thru three above are replaced by other models of D062 demand and leadtime processes, alternate formulas for computing optimum reorder levels are obtained. This paper presents the results of simulation experiments to evaluate the relative cost effectiveness of several of these alternate "optimum" computations compared to current D062 formulas.

The paper is organized as follows: Section I presents additional background for this study. This section describes the general formulas to be evaluated, the item samples used to simulate the D062 system, and the features of the simulation experiment. In Section II, we present general observations concerning the demand patterns and inventory system behavior for each of these item samples. In Section III, we present measurements of the sensitivity of the INSSIM model to several key parameters. Simulation results for Policy Code 20, to be defined later, are also discussed in this section. In Section IV we present cost effectiveness curves which quantify the relative strengths and weaknesses of each of the proposed formulas. Finally, in Section V we present the general conclusions obtained from this study.

Inventory Management Policies for Evaluation

Six basic inventory management policies were selected for detailed evaluation in this study. A brief discription of these policies and the associated "Inventory Management Policy Code" which was used to identify these runs in subsequent simulation experiments are presented in Table I-1. Let us now consider each of these formulas in more detail.

Policy Code 10: The Current D062 Formulas

As shown the table, Policy Code 10 denotes the current D062 inventory management formulas. These computations are based on formulas originally developed by Presutti and Trepp (1970). These authors consider the problem of determining order quantities and reorder points for each item in a single-echelon, multi-item, continuous review inventory system so as to minimize total system holding and shortage costs subject to a constraint on the average number of units in a backorder position. Presutti and Trepp begin by assuming that demand in a leadtime is normally distributed. However, they then utilize the Laplace distribution to approximate the normal. With this substitution, Presutti and Trepp obtain closed form expressions for the optimum order quantity and reorder point. For convenience, we refer to these resulting formulas as the PT-formulas. Subsequent simulation studies using actual demand history for Air Force items showed that the PT-formulas were significantly more cost effective than the inventory level

Table I-1

Inventory Management Policy Codes

Code	Inventory Management Policy
10	Current D062 Formulas
20	Current D062 Formulas, with outliers excluded from demand and variance estimates
60	Current D062 Formulas, with adjustments to standard deviation of lead time demand to account for lead time variability
70	Scaled Negative Binomial reorder point calculations, with no bounds on safety level
80	Constant Leadtime Exponential Forecast Error model, with no bounds on safety level
90	Exponential-Gamma Forecast Error Model, with no bounds on safety level

computations then in use; that is, the PT-formulas provided lower levels of backorders for a given investment in inventory than the previous formulas, or, conversely, a given backorder level could be achieved with the PT-formulas for a smaller investment in safety stocks.

The basic calculations used to implement the PT-formulas in the D062 system are shown in Figures I-1 thru I-3. Figure I-1 presents formulas for obtaining the demand rate, average requisition size, and standard deviation estimates required in the PT-formulas. These estimates are based on moving averages involving at most 8-quarters of historical demands. As shown at the bottom of the figure, these historical averages may then be modified to account for forecast changes in flying program activity.

As shown in Figure I-1, the standard deviation of demands in the leadtime σ is a major parameter in the current D062 safety level calculations. However, demand in a leadtime is not presently recorded in the D062 system. Consequently, the parameter σ must be estimated from available data. Let QMAD denote the Mean Absolute Deviation associated with the demands observed in each of the last eight quarters, and let t denote the expected replenishment leadtime for an individual item (i.e. t represents the sum of administrative and procurement leadtimes). Then in D062 the parameter σ is estimated from the following formula:

Figure I-1 Forecast and Standard Deviation Calculation Formulas used in Subroutine FOR576.

Quarterly Demand Rate:

$$\text{FORCST} = \sum_{n=1}^{N} \frac{(\text{Gross Demand}_n) - (\text{serviceable returns}_n)}{N}$$

where N equals the number of quarters of available data.

Annual Demand Rate:

ADR(N) = 4. * FORCST

Average Requisition Size:

$$\text{REQSIZ(N)} = \frac{\sum_{n=1}^{N} \text{GROSS DEMANDS}_n}{\sum_{n=1}^{N} \text{FREQUENCIES}_n}$$

Quarterly MAD:

$$\text{MAD}_Q = \sum_{n=1}^{N} \left| \text{Actual Quarterly Demand}_n - 3 * \text{QDR} \right| / N$$

where N number of quarters of data

Standard Deviation of Lead Time Demand

SIG = 0.5945* MADQ* (0.82375 + 0.42625* Leadtime Months)

Program Factor Adjustments

Let PF = Program Factor = Ratio of the forecast flying program in the next two years to the actual program in the last two years.

Then if PF is not equal to 1.00,

Replace ADR(N) by ADR(N)*PF

and Replace SIG by $\text{SIG*PF}^{0.85}$

$$(1) \quad \sigma = 0.5945 * QMAD * (0.8235 + 0.42625 * t)$$

This estimation formula is based on a calculation suggested by Robert G. Brown (1967). The calculation assumes that the lead-time t is known with certainty, and it adjusts for the fact that forecasts of demand rates are based upon moving average estimates.

Figure I-2 illustrates the formulas used to compute the Economic Order Quantity (EOQ). This quantity represents the number of units to be ordered when available stocks reach the reorder level. As shown in the figure, two basic procurement methods are utilized to purchase the items managed by the D062 system. One method applies to purchases which are less than a critical breakpoint, denoted by the symbol "CSTBRK" in the figure, while the second procurement method refers to purchases of large dollar magnitude. Less procurement effort, and consequently lower ordering costs, are associated with small purchases. As shown in Figure I-2, a small purchase order quantity is first computed. If this order quantity is less than the dollar breakpoint CSTBRK, that order quantity is adopted. Otherwise, the large purchase cost to order parameter is used to compute the EOQ quantity.

After the tentative EOQ is computed, this quantity is bounded to lie between two bounds specified by management. First, a lower bound is placed on the EOQ quantity to prevent extremely high frequencies of reorders for high dollar activity items.

Figure 1-2

Economic Order Quantity Calculations

LET
Q = Order quantity
RMR = Monthly demand rate (units)
ADR = Annual demand rate (units)
COSORD(I) = Cost to place an order, where
I = 1 indicates small purchase and
I = 2 indicates large purchase methods
CSTBRK = Dollar breakpoint distinguishing large and small purchase methods
COSHLD = Cost to hold one dollar of stock in inventory for one year
UC = Item unit cost

then

$$Q = \sqrt{\frac{2 * COSORD(1) * ADR}{COSHLD * UC}} \quad \text{Provided Q.C} < \text{CSTBRK}$$

Otherwise,

$$Q = \sqrt{\frac{2 * COSORD(2) * ADR}{COSHLD * UC}}$$

EOQ Size Limits

For the order quantity Q computed above,

if Q > EOQMAX *RMR, set Q = EOQMAX * RMR
if Q < EOQMIN *RMR, set Q = EOQMIN * RMR
if Q < 1, set Q = 1

On the other hand, an upper bound is also placed on the EOQ to prevent unrealistically large order quantities--representing many years of supply--to be brought into the Air Force supply system. This upper bound is to protect against unacceptably high obsolescence rates which might occur if program levels unexpectly decline.

Figure I-3 illustrates the formulas used to compute safety levels in the D062 system. As shown in the figure, an important element in this computation is a priority factor Z. At present, this priority factor is set equal to the square root the average requisition size for an individual item. As shown in the Figure, a tentative safety level is computed in step (c). This tentative safety level is then bounded to be no less than zero, and no more than the upper bounds specified in step (d). Specifically, the safety level is limited to be no more than the lesser of either (a) the expected demands in the forecast leadtime, or (b) three times the standard deviation of leadtime demands.

Policy Code 20

In studying the detailed demand histories of individual D062 items, we observed that many items contained large "spikes", i.e. quarters of very large demand which did appeared inconsistent with demands both before and after the occurrence of the spike. When such spikes occur, both reorder levels and reorder quantities computed by the PT-formulas jump significantly, and may trigger

Figure I-3

Safety Level Calculations

LET SL = Safety level
Q = Order quantity (the EOQ)
RMR = Monthly demand rate (units)
RLT = Expected number of demands in a lead time
Z = A priority factor as defined in Table I-3
σ = Standard deviation of demand in the lead time

then

(a) For a given policy, set Z as defined in Table I-3

(b) Compute K,

$$K = 0.707 \text{ X LN} \left[\frac{\begin{pmatrix}\text{Implied}\\ \text{Shortage}\\ \text{Factor}\end{pmatrix} \quad 1\ \sigma.\ (1\text{-EXP}\ (-\sqrt{2}\ Q/\sigma))}{2. \begin{pmatrix}\text{Holding}\\ \text{Cost}\end{pmatrix} \begin{pmatrix}\text{Unit}\\ \text{Cost}\end{pmatrix} \cdot Z \cdot \sqrt{2}\ Q} \right]$$

(c) Tentative safety level = SL = K * σ
If SL < 0, reset SL = 0

(d) If upper bounds are to be applied,

(d.1) If SL > RLT, reset SL = RLT

(d.2) If SL > 3*σ, reset SL = 3*σ

new buys of material. If demands return to their previous levels in subsequent quarters, this material often becomes surplus. Consequently, we hypothesized that inventory management effectiveness might be improved by using forecasting methods which test for the presence of spikes and which eliminate unreasonably large demand observations from the forecasting calculations. Formula Code 20 uses such a test for outliers. Under this Policy Code, we first determine the largest demand observed in the last eight quarters. We then compute the average demand rate and the MAD of the seven remaining data points. If the largest observation is within four times the MAD of the average rate, that large observation is included in the forecast calculations. Otherwise, the large observation is declared an "outlier", and it is ignored in the demand and MAD estimates. Once the demand rate and MAD estimates are obtained, the standard D062 EOQ and safety level calculations are performed. Thus, Policy Code 20 differs from Policy Code 10 in its estimates for the mean and MAD of demands, but is otherwise identical to the current D062 formulas.

Policy Code 60

As shown in Table I-1, Policy Code 60 utilizes the current D062 forecasting, safety level, and EOQ formulas, but adjusts the estimate of the standard deviation of leadtime demand to account for leadtime variability. As noted above, the current D062 estimate for the standard deviation of leadtime demand σ

assumes that leadtime is known with certainty. However, if leadtimes are variable, the above estimates are no longer valid. One approach for estimating the standard deviation of leadtime demand with leadtime variability considered is as follows: First, let X_i denote the demand in period i, and let L denote the number of periods in the leadtime. Then the total leadtime demand is given by:

$$(2) \quad T = X_1 + X_2 + \ldots + X_L$$

Let u_x and σ_x denote the expected value and standard deviation of X_i, and let u_L and σ_L denote the expected value and standard deviation of leadtime. If we assume that the X_i are independent random variables, and that the actual leadtime L is independent of demand, then the standard deviation σ_T of demand in the leadtime is given by

$$(3) \quad \sigma_T = \sqrt{u_L \sigma_x^2 + u_x^2 \sigma_L^2}$$

In our simulation experiments, we used this formula to estimate the standard deviation of demand in a leadtime. The D062 formulas illustrated in Figures I-1 and I-2 were then used to compute order quantities and safety levels for individual EOQ items.

In the simulation experiments to be discussed in Section IV, we assummed the lead times of all items were gamma distributed with a coefficient of variation of 35%. We used this fact directly in (3) to estimate the standard deviation of leadtime σ_L. In practice, this parameter would have to be estimated from available data, and would be subject to substantial estimation errors. Thus, this Policy Code 60 rule should perform better in our simulation studies than it would perform if implemented into the D062 system.

Policy Code 70

Formula Code 70 uses the scaled negative binomial probability distribution as a model for demands in a leadtime. This model is based upon work by Nahmias and Demmy (1981). These authors consider a situation in which requisition sizes are described by the logarithmic distribution and in which customers arrive according to a Poisson process. Further, they assume that leadtimes are gamma distributed. These assumptions appear to be reasonable approximations to available D062 demand and leadtime data. With these assumptions they derive the probability distribution for demands in the leadtime. They call this model the Logarithmic-Poisson-Gamma (LPG) distribution. Unforturnately, evaluation of data points for the LPG distribution require substantial computational effort. However, in Reference 4 Demmy and Nahmias found that the scaled negative binomial distribution provides a good approximation to the LPG for a wide range of

parameter values. Consequently, the scaled negative bionomial model was selected for testing in these experiments.

Policy Code 80

Reference 3 presents the results of a statistical analysis of the distribution of forecast errors associated with current D062 demand forecasting procedures. In this reference, it is observed that a combination of exponential functions provides a better approximation to the distribution of forecast errors than the normal probability model. In Policy Code 80, we assume that the leadtime is known with certainty, and the exponential forecast error model is used to compute percentage points for the distribution of demand in a leadtime. Details of the exponential forecast error model, and a comparision of this model with the distribution currently employed in D062 may be found in Reference 5.

Policy Code 90

This inventory management policy utilizes the exponential forecast error model discussed for Policy Code 80, but assumes that leadtimes are gamma distributed. In this model, the distribution of forecast errors in a given leadtime t is weighted by the probability of occurence of the specific leadtime value t.

This results in a leadtime demand distribution with a higher variance than that given by Policy Code 80. A detailed discussion of the formulas for Policy Codes 80 and 90 may be found in Reference 5. In addition, Reference 5 presents a number of plots which describe the sensitivity of these formulas to changes in several important parameters.

Support Level Codes and Run Codes

An important input to all of the inventory management policies that were tested is the implied cost of a shortage, which we shall denote by the symbol C. If C is large, safety stocks should be high to keep shortage costs to a reasonable level. On the other hand, if C is small, the penalty for shortages is not as great, and less safety stocks should be procured.

Table I-2 presents the shortage cost factors used in this study, as well as an associated "Support Code." The Support Code was used to identify given simulation runs in post-processing calculations. Specifically, each simulation run was assigned a "Run Code" of the form XXYY, where XX denotes a specific inventory policy code from Table I-1 and YY denotes a specific Support Code from Table I-2. Thus, the run code 7030 represents a scaled negative binomical calculation (Policy 70) using an implied shortage cost of 500 (Support Code 30). Similarly, run code 1030 represents the current D062 formulas (Policy 10) using an implied

Table I-2

Support Level Codes

Support Code	Shortage Cost Factor
10	.1
12	25.
15	100.
20	250.
30	500.
40	750.
50	1000.
60	2000.

shortage cost of 500.

Inventory Management Parameters

Each of the inventory management policies requires several inputs in addition to the implied cost of a shortage. Table I-3 presents the parameter values that were used in all Policy 10 runs. With the exception of bounds on the safety level, these same parameter values were used for all of the other Policy Code simulation runs. However, as noted above, the safety level bounding rules varied among the policies.

Table I-3

Inventory Management Parameters

Cost to Hold Inventory	20% of unit cost per year
Order Cost for Small Purchases	$300/order
Order Cost for Large Purchases	$500/order
Small Purchase/Large Purchase Breakpoint	$19,500/order
Minimum EOQ	6 months supply
Maximum EOQ	36 months supply
Minimum Safety Level	0
Maximum Safety Level	Minimum of expected lead time demands, or three times the standard deviation of demand in a lead time.
Support Level	1 month supply

Evaluation Approach

We used the Inventory System Simulator (INSSIM) to evaluate the relative cost effectiveness of each of the proposed formulas discussed above. The Inventory System Simulator provides a detailed description of the Economic Order Quanitity Buy Computation System (D062), and utilizes actual D062 demand histories to drive the simulation process. For this study, we modified the original version of INSSIM to provide the capability to simulate random leadtimes and to provide a more detailed description of the requisition generation process. A detailed description of the original INSSIM model may be found in References 6 and 7, while Reference 2 describes the new routines which were developed for this study. Let us now consider the detailed rules which are incorporated in the simulation scenario selected for this study.

The Simulation Scenario

As noted above, the Inventory System Simulator provides a detailed description of the D062 inventory management system. Major rules which were incorporated in INSSIM for this study are the following:

1. The total number of units demanded in each simulated quarter exactly equals the D062 historical values for each simulated item. However, Monte Carlo techniques are used to generate the specific sizes of individual requisitions. Both high and low priority requisitions are simulated, and there is a 50% chance that any given requisition is a high priority demand. Individual requisitions within a given quarter are obtained from a negative binomial distribution. Because of the lack of accurate requisition data during the earlier quarters of the INSSIM Data Bank, requisition size parameters are derived from the 12 most recent quarters of demand history.

2. Forecast of item demand rates and associated safety levels, reorder points, and order quantities are updated each quarter. Forecasts are based on an eight quarter moving average, with proportional adjustments for forecast changes in flying program activity. With the exception of Policy 20, all inventory management rules evaluated use the current D062 forecasting formulas. Policy 20 deletes outliers from the demand rate calculation, but is otherwise identical to the D062 calculation.

3. Safety stocks and EOQ quantities are based upon specific inventory management formulas which are specified as input to the simulation. The basic formulas used are identified above. Safety stocks are then computed and bounded according to management parameters specified as input to the simulation. As noted above, Table I-1 presents the current D062 inventory policies considered in this study, while Figures I-1 thru I-3 define the specific forecasting, EOQ, and safety level formulas. EOQ quantities are bounded to lie between 6 and 36 times the forecast monthly demand rates for all inventory management policies.

4. Order processing costs, inventory holding costs, and item purchase costs are assumed known and constant throughout the simulation.

5. Leadtimes are assumed to be gamma distributed with a mean equal to the INSSIM Data Bank leadtime value. The coefficient of variation of leadtimes is assumed to be .353 for all items simulated.

6. Initial on hand stocks are set equal to the expected demand in the leadtime in every item simulated, and initial on order stocks are set equal to zero. This assumption assures that no item is in an "excess" position in the beginning of the simulation run. However, it also means that any item with a positive safety level will generate a "buy" during the first week of simulation.

Simulation Dynamics

A total of 38 quarters of data were available from the D062 history records. This data covered the period beginning with the first quarter of CY71 and continued through CY79. Eight quarters of this data were used to initialize the historical arrays and demand rate estimates, and 30 quarters were used to simulate the dynamic behavior of the system. Consequently the simulation evaluates how each of the proposed rules would have performed had they been employed beginning with the first quarter of CY73.

Item Samples

As noted above, the Inventory System Simulator is driven by actual D062 demand histories. For this study, four samples of up to 500 items each were selected from the historical records in the INSSIM Data Bank. The criteria used to select these items are presented in Table I-4. As shown in Table I-4, two samples were selected from Sacramento Air Logistics Center (ALC), while two samples were selected from D062 history records from Oklahoma City ALC. A "high" and "low" activity demand sample was selected from each ALC. Items in the high activity sample were required to have demands of $5000 per year or more during the CY71-72 period, while items in the low demand category were required to have demand activity of less than $5000 per year during the CY71-72 interval.

In previous studies, we found that the forecast error characteristics associated with F-104 and F-5 aircraft differ significantly from the error characteristics associated with the other aircraft represented in the INSSIM Data Bank records. Consequently, all items which were associated with F-104 and F-5 aircraft were excluded

Table I-4

Characteristics of Item Samples

Sample Code	Air Logistics Center	Number of Items	CY71-72 Demands
SM.H	Sacramento	450	greater than $5000/yr
SM.L	Sacramento	500	less than $5000/yr
OC.H	Oklahoma City	500	greater than $5000/yr
OC.L	Oklahoma City	500	less than $5000/yr

Note: Items associated with F104 and F5 aircraft were excluded from all samples.

from the samples. We originally planned to have 500 items included within each sample. However, once the F-104 and F-5 items were deleted from the Sacramento high activity sample, less than 500 items remained. Consequently, we elected to include only 450 items in this particular sample, but a total of 500 items in all three remaining samples.

Table I-5 presents statistics on the aggregate 30 quarter demand activity associated with each of the item samples. As shown in the table, the high activity samples have significantly greater demands that the two low demand activity demand samples. For the Oklahoma City high activity sample, a total of 343173 requisitions representing approximately 825,000 units of demand were simulated. This demand had a total dollar value of $55,153,000. On the other hand, the SM.H sample had over 161,000 requisitions representing over $36,570,000 of demand during this period. Finally, the low activity samples OC.L and SM.L had much lower levels of activity.

The vast majority of current (1981) D062 items would fall into a low demand category similar to that represented by the samples OC.L and SM.L. However, the majority of current D062 procurement expenditures are associated with high activity items similar to those included in the samples in OC.H and SM.H. By using four samples, we hope to obtain information on any differences in performance of the alternate formulas among these important categories of items.

Table I-5

Demand Activity in 30 Quarters

Sample	No. of Items	No. of Requisitions	No. of Units (1,000s)	Total Dollar Value ($1,000s)
OC.H	500	343,173	825	55,153
SM.H	450	161,768	301	36,570
OC.L	500	77,335	138	2,257
SM.L	500	32,461	44	1,311

Simulation Results

Each item sample was used in at least five separate simulation runs for each of the inventory management policies tested. A large number of tables and graphs were then developed to summarize our results. In the next section, we discuss general observations that apply to all the inventory policies and item samples used in this study. Plots of the behavior of demands and of on order and excess stocks under current D062 inventory management rules are also presented.

Section II

General Observations

In this section, we discuss the general patterns of inventory behavior applicable to all of the inventory policies considered in this study. In Sections III and IV, on the other hand, we present comparisons among the different inventory management policies.

Item Sample Characteristics

As discussed in Section I, four item samples were selected for this study. High and low activity samples of up to five hundred items each were selected from the Oklahoma City and Sacramento Air Logistics Centers (ALC). We represent these four item samples by the symbols OC.H, SM.H, OC.L, and SM.L, respectively. All four item samples were selected from the INSSIM Data Bank. Consequently, to be included in this stuty an item must have had at least one demand in the CY71-72 interval, and the item must have been listed in the D062 inventory system records at the same Air Logistics Center throughout the CY71-79 interval. Consequently, no new items were included in the samples used in this study.

Items included in the INSSIM Data Bank provide support for 24 different USAF aircraft. All but one of these aircraft, the F-5, experienced significantly declining programs throughout the decade of the 70s. At the beginning CY71, the Vietnam War was under way, and both flying programs and EOQ usage were significantly higher than during the last half of the decade. In

addition, a number of the aircraft associated with INSSIM Data Bank items were phased out of the USAF inventory during this period. Aircraft whose flying programs went to zero during this period include the C-118, C-121, F-102, and T-29. In addition, the flying program of the F-104 dropped to zero during the first quarter of CY-76, but increased significantly in the third quarter of CY-76 to support Foreign Military Sales activity. As noted earlier, we have found that forecast errors for items associated with F-5 and F-104 aircraft are significantly higher than for other INSSIM items. Consequently, all F-5 and F-104 items were excluded from the item samples used in this study.

Considering the general decline in flying program activity, its not surprising that the demand patterns of all four item samples used in this study drop during the 30 quarter simulation. For example, Figures II-1 thru II-4 present the dollar value of demands observed for the OC.H, SM.H, OC.L, and SM.L samples during the CY73-79 interval. As shown in Figure II-1, the dollar value of demands for OC.H items dropped significantly during the CY73-75 interval, but remained fairly stable for the remainder of the CY73-79 interval. On the other hand, the dollar value of demands associated with the SM.H sample presented in the Figure II-3 show a significant and continuing decline throughout the CY73-79 interval. For the low activity samples OC.L and SM.L, the dollar value of demand is more stable, but is slightly lower during the later portion of the CY73-79 interval than during the first eight quarters of this period.

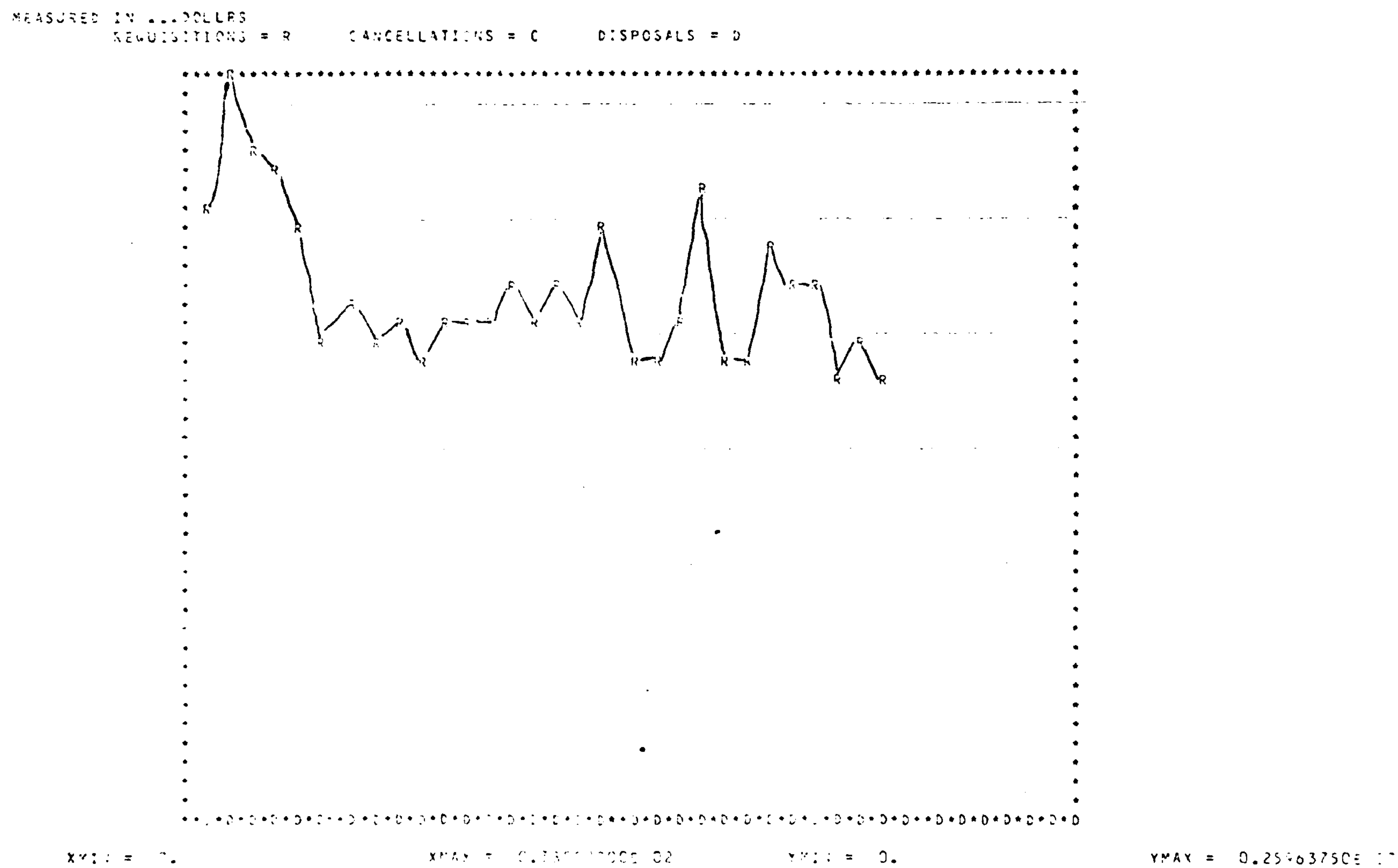
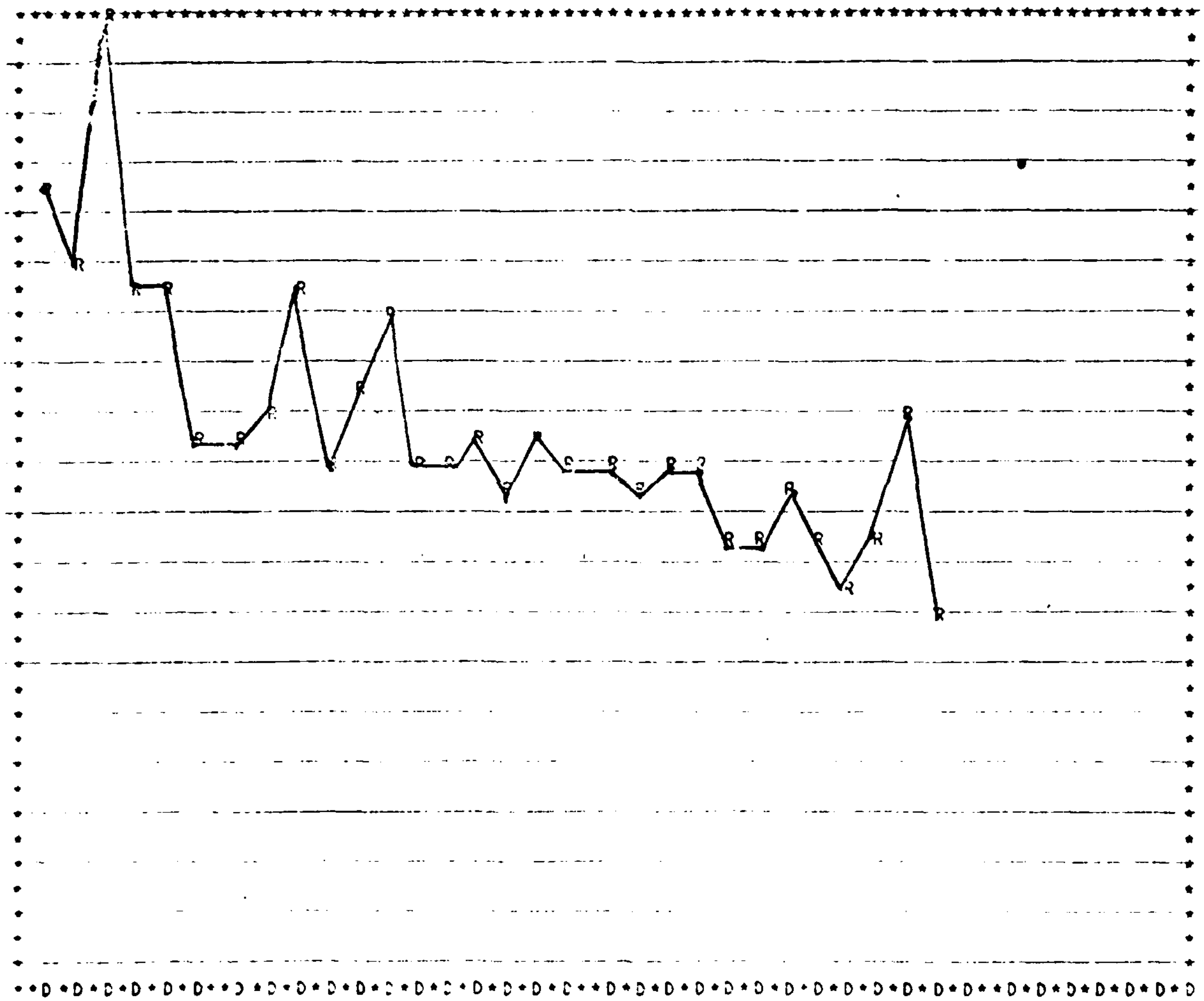


Figure II-1. Dollar Demand per Quarter for Sample OC.H.

MEASURED IN ...DOLLRS
REQUISITIONS = R   CANCELLATIONS = C   DISPOSALS = D



XMIN = 0.   XMAX = 0.38000000E 02   YMIN = 0.   YMAX = 0.20990810E 07

Figure II-2. Dollar Demand per Quarter for Sample SM.H.

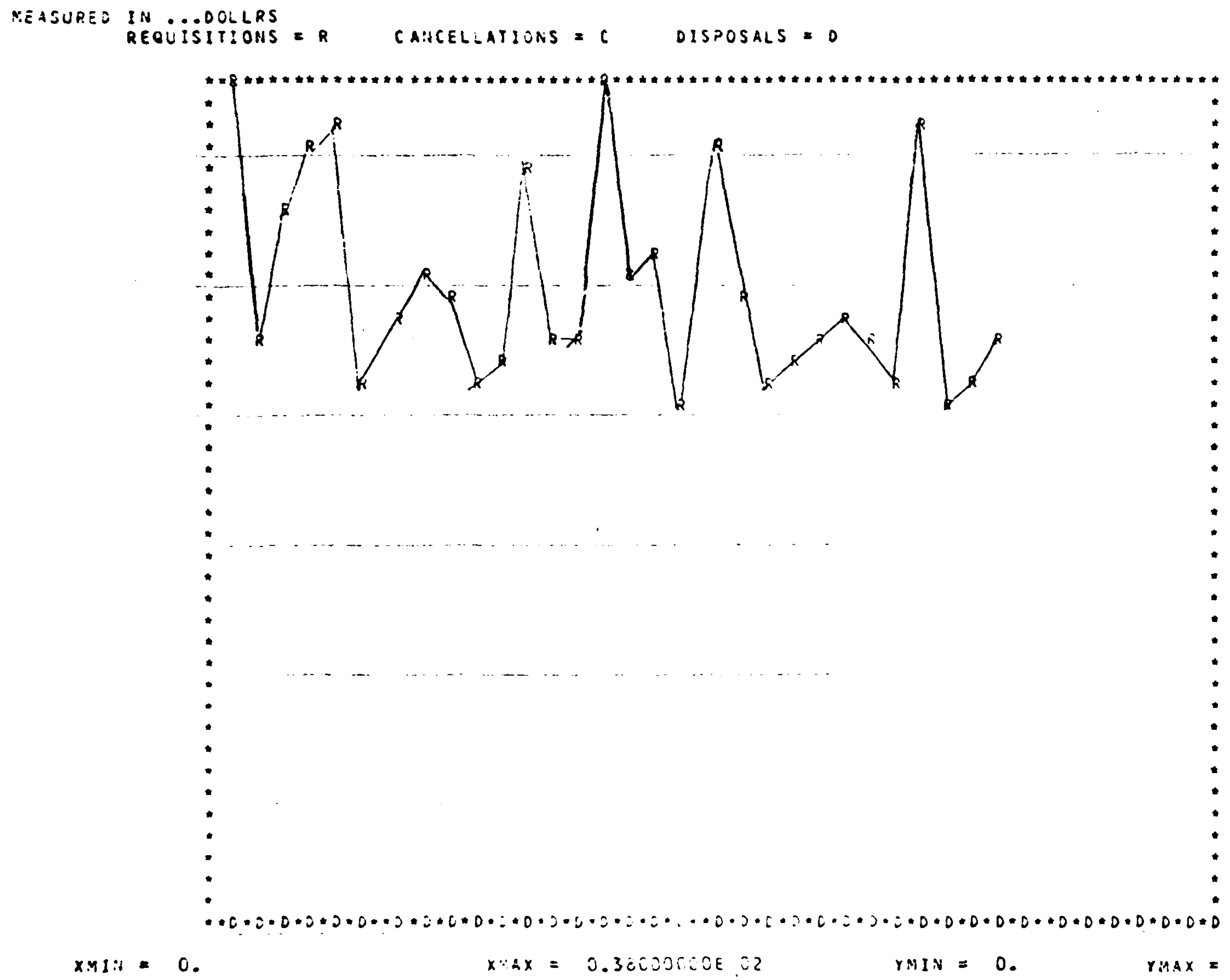


Figure II-3. Dollar Demand per Quarter for Sample OC.L.

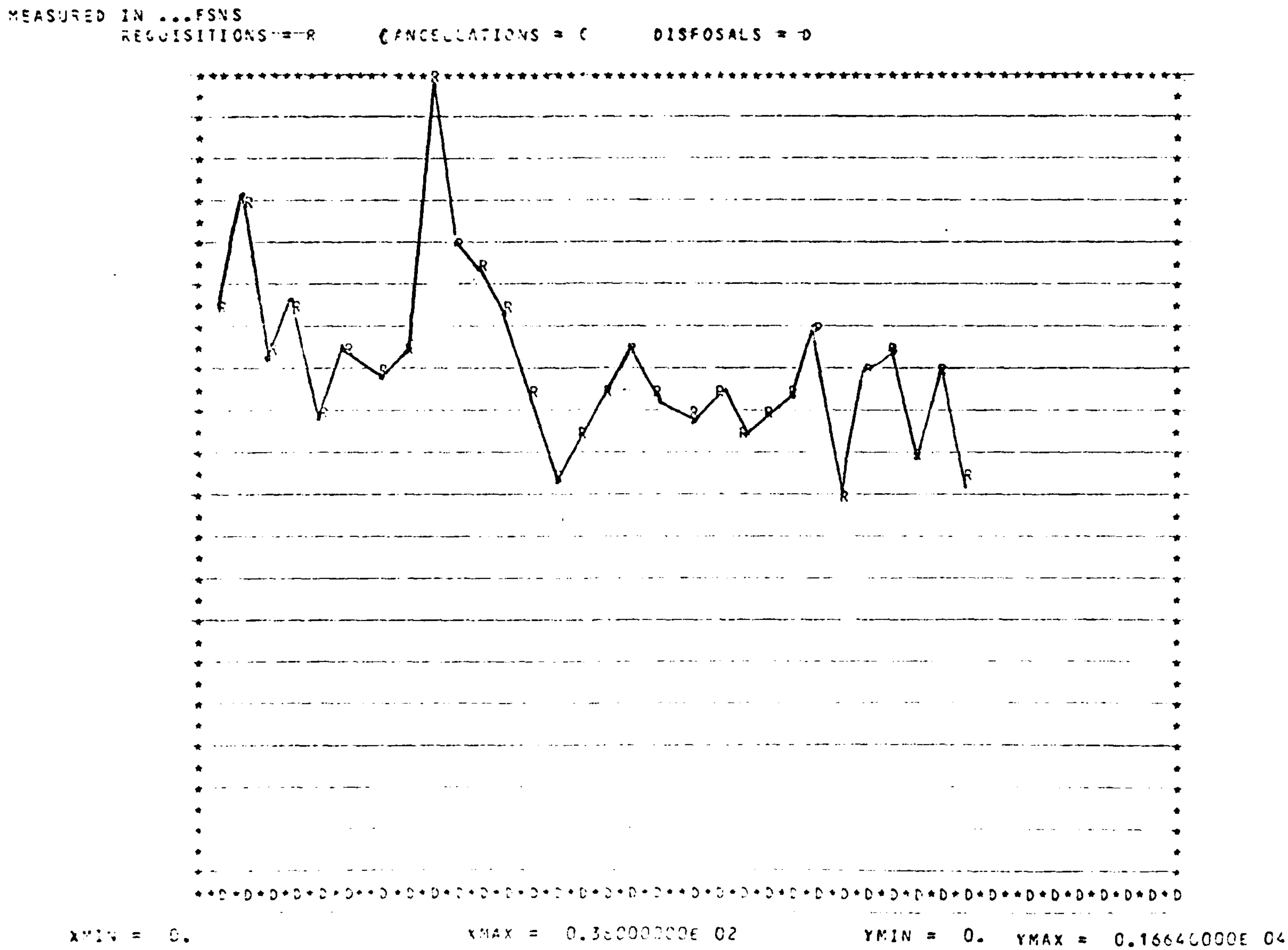


Figure II-4. Dollar Demand per Quarter for Sample SM.L.

Monte Carlo Generation of Requisition Sizes

In the Inventory System Simulator, the number of units generated in a given quarter exactly equals the historical demand values recorded in the INSSIM Data Bank for that particular item. However, Monte Carlo techniques must be used to generate the specific requisition sizes and to determine the precise time of requisition arrival within a given quarter. In this study, we assumed that requisition sizes were described by a negative binomial distribution, and the parameters of this distribution were estimated from the 12 most recent demand values associated with a given item in the INSSIM Data Bank. Figures in II-5 thru II-8 present plots of the total number of requisitions generated each quarter for samples OC.H, SM.H, OC.L, and SM.L, respectively. As may be seen from the figures, these aggregate requisition counts roughtly parallel the total dollar demands presented in Figures II-1 thru II-4.

On Hand and Excess Stocks

Figures II-9 and II-10 plot the behavior of on-hand and excess stocks observed in simulating Run Code 1030 for item sample OC.H. Using the coding scheme defined in Tables I-1 and I-2 of Section I, this Run Code represents Policy Code 10 (the current D062 inventory

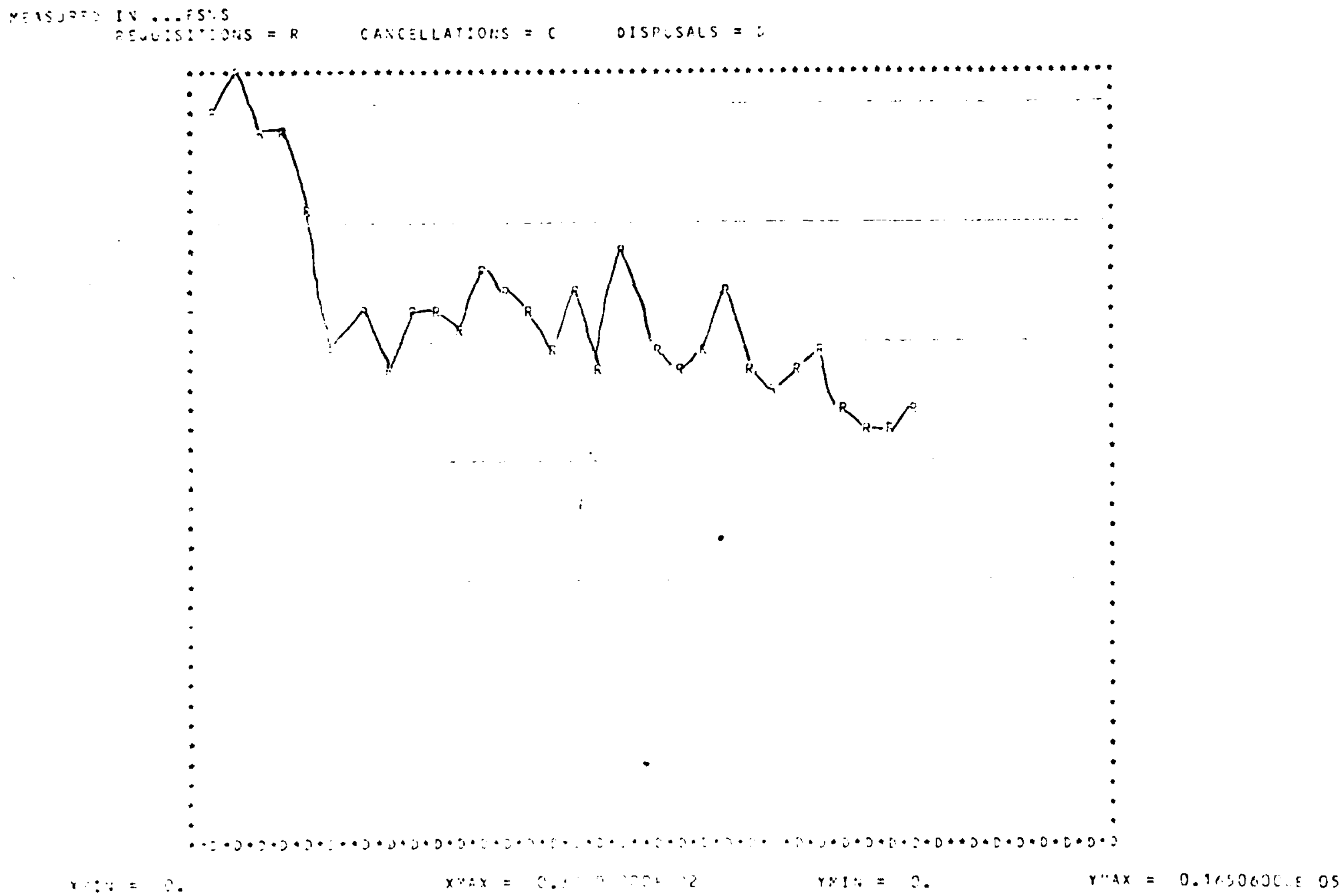


Figure II-5. Requisitions per Quarter for Sample OC.H.

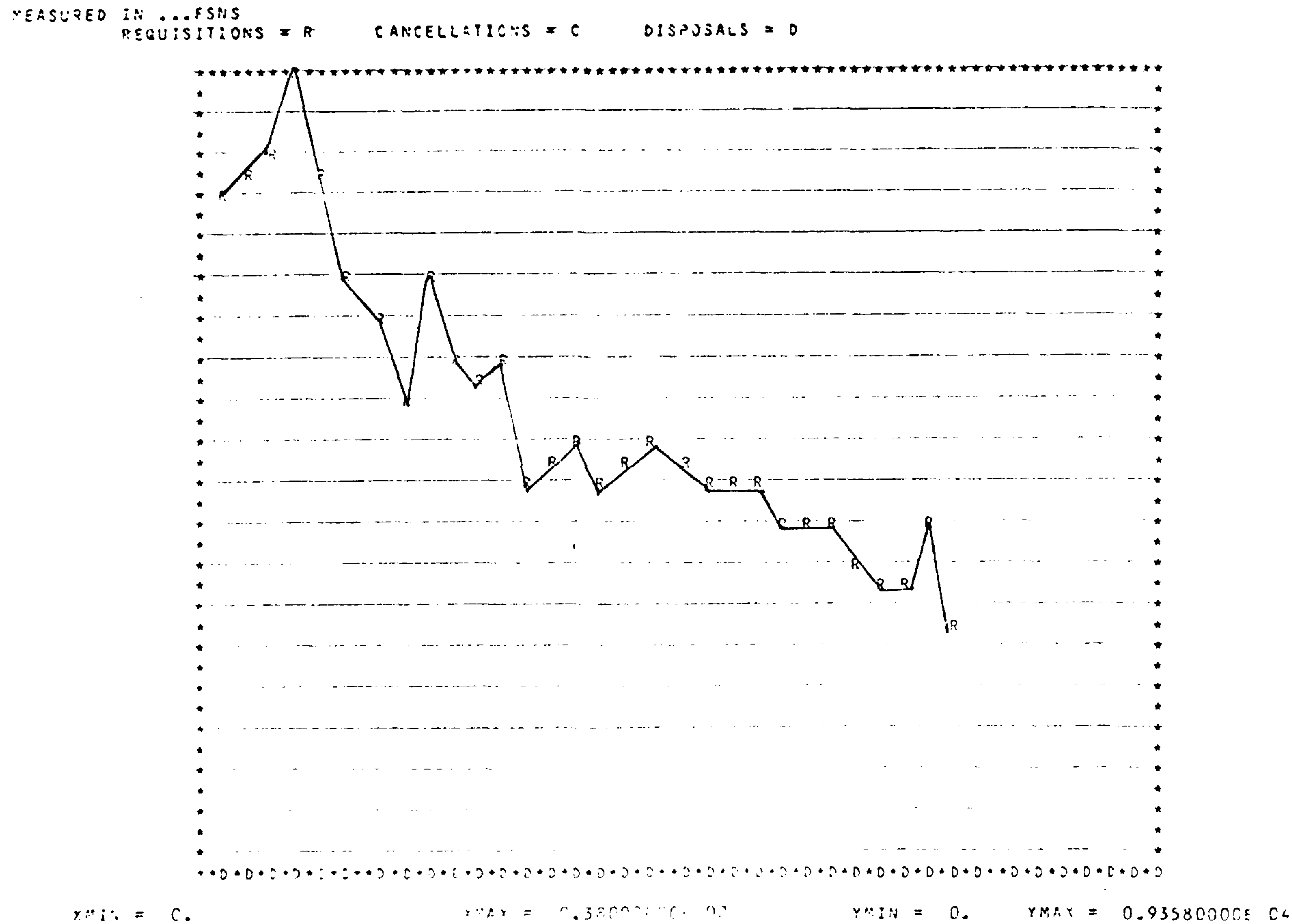


Figure II-6. Requisitions per Quarter for Sample SM.H.

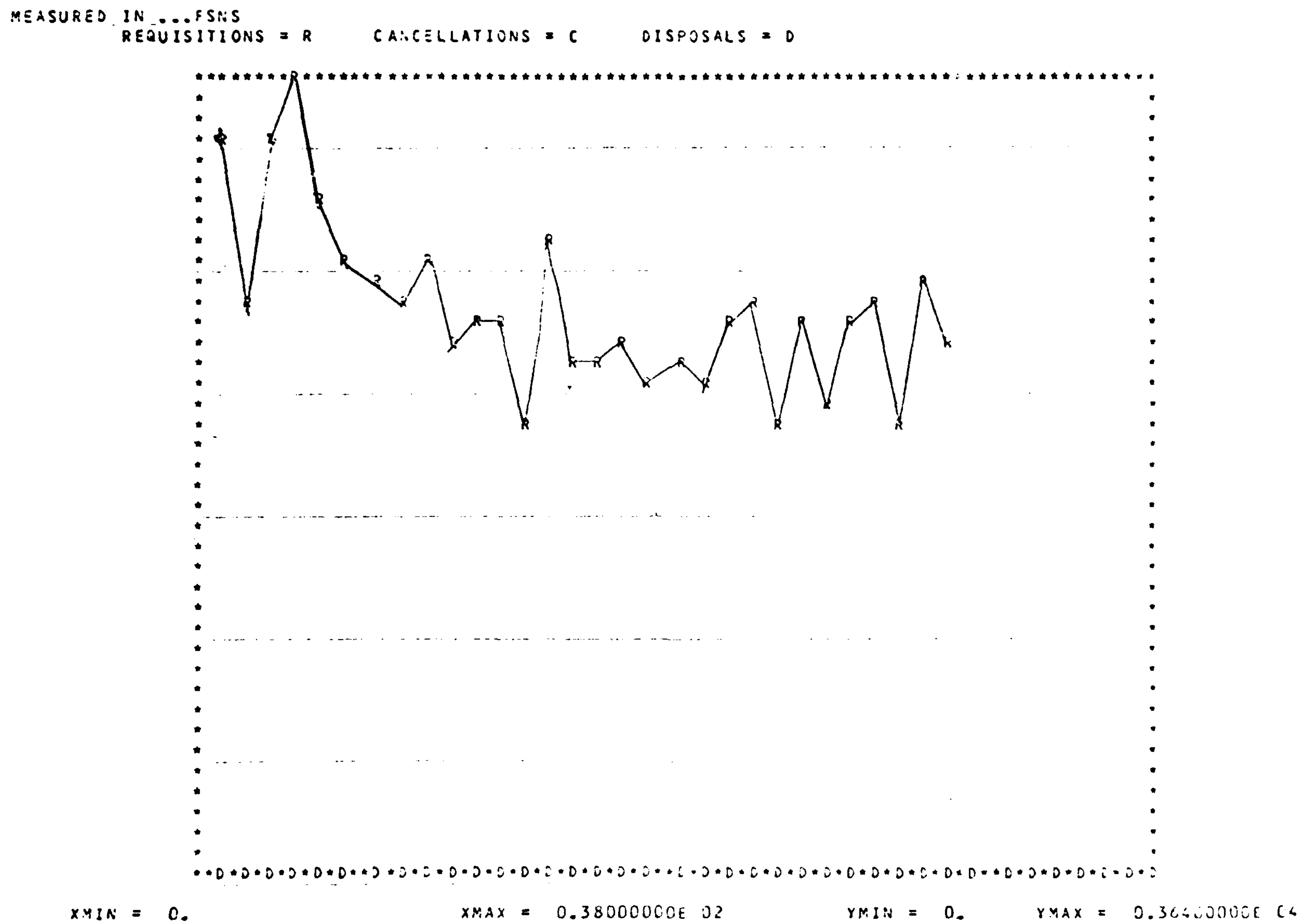


Figure II-7. Requisitions per Quarter for Sample OC.L.

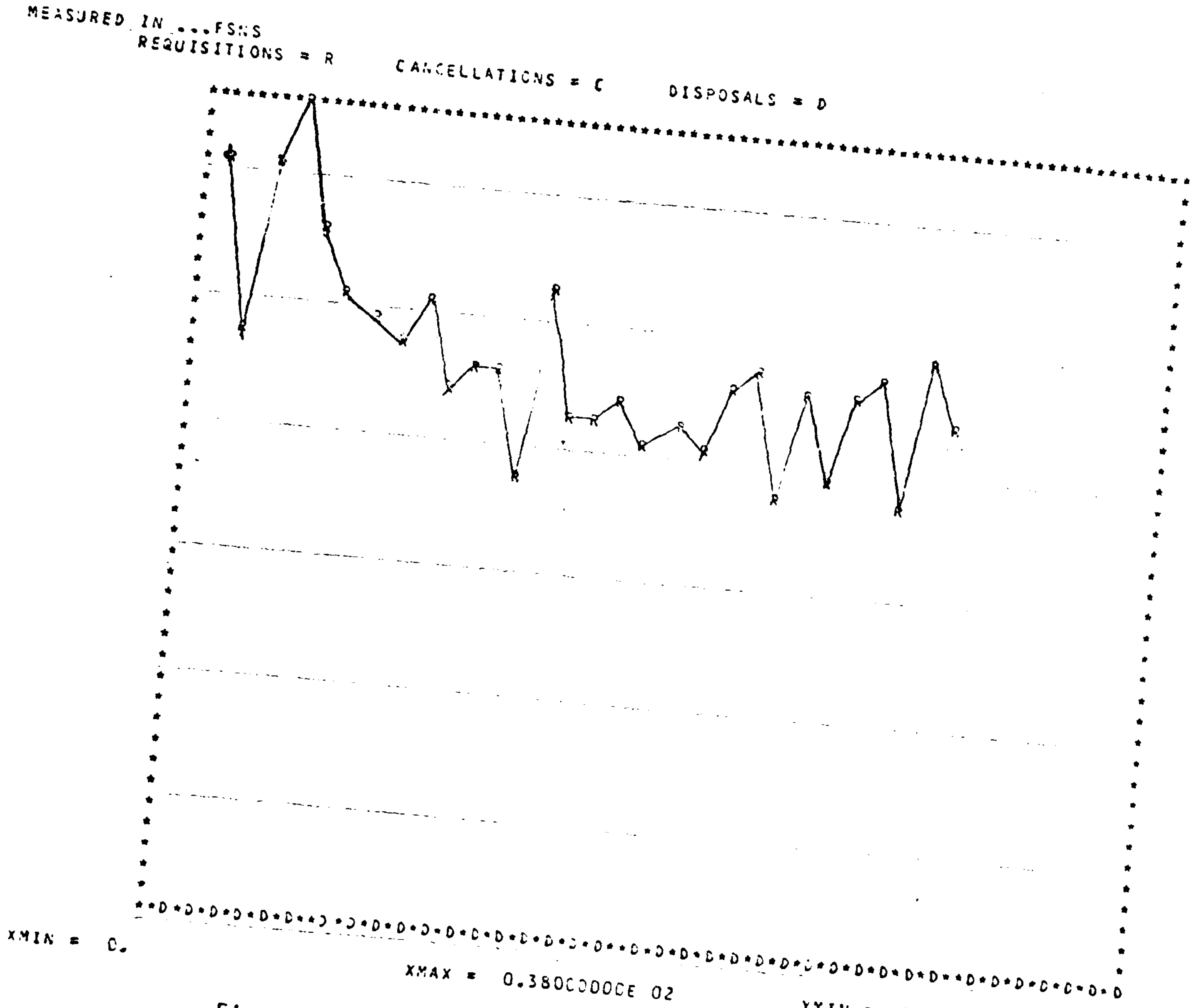


Figure II-7. Requisitions per Qua

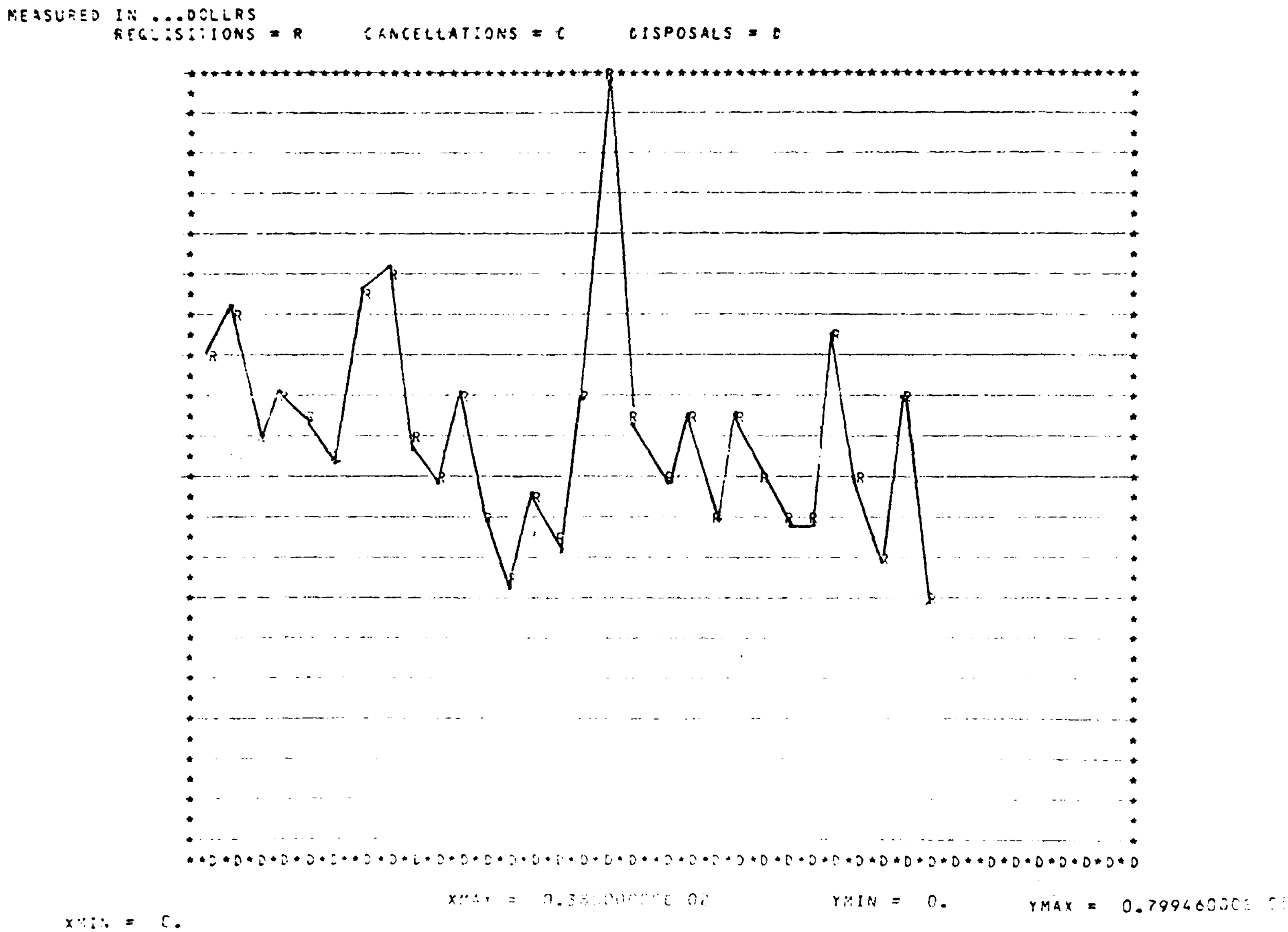


Figure II-8. Requisitions per Quarter for Sample SM.L.

management formulas), with a Support Code of 30, corresponding to an implied shortage cost of \$500. Figure II-9 plots the simulated behavior of on-hand and on-order stocks, and backorders throughout the CY 73-79 simulation. As noted earlier, in the simulation initial on-hand stocks are set equal to the expected demand in a lead time, and all on-order stocks are set equal to zero. Consequently, all items with a positive safety level generate new buys during the first period of the simulation. Also, no item is in a backorder or excess position at simulated time zero. As shown in Figure-9, this results in an initial surge of ordering activity followed by a growth in on-hand stocks as these initial orders are delivered. The ordering pattern declines in the later portion of the simulation due to the decreasing demand activity of a majority of sample items.

Figure II-10 presents a plot of the combined stocking objective (denoted by "O") observed during the 30 quarter simulation interval for all items included in the OC.H sample. This curve represents the sum of the Air Force Acquisition Objectives (AFAO) for all items at a given point in time. By definition, the AFAO equals the sum of the reorder level requirement and the EOQ. If demand forecasts were perfect, the AFAO is the maximum amount of stock that should be on-hand and on-order at a given point in time. Thus, the AFAO curve represents an upper limit to the amount of stock desired in the on-hand/on-order pipeline. As shown in Figure II-10, the desired stocking objective decreased as the simulated time progressed.

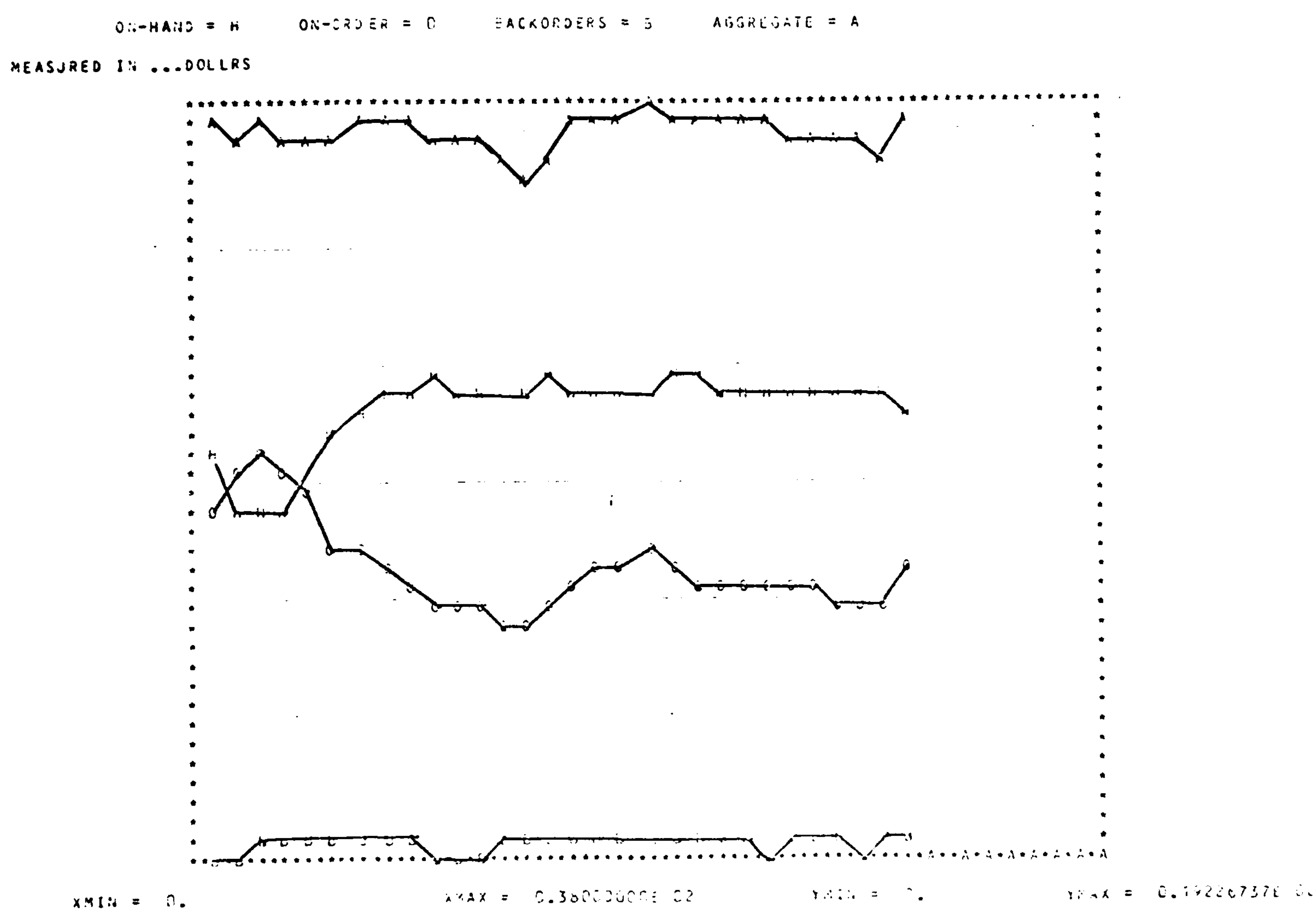


Figure II-9. Dollar Value of On-Hand and On-Order Stocks for Sample OC.H, Policy 1030.

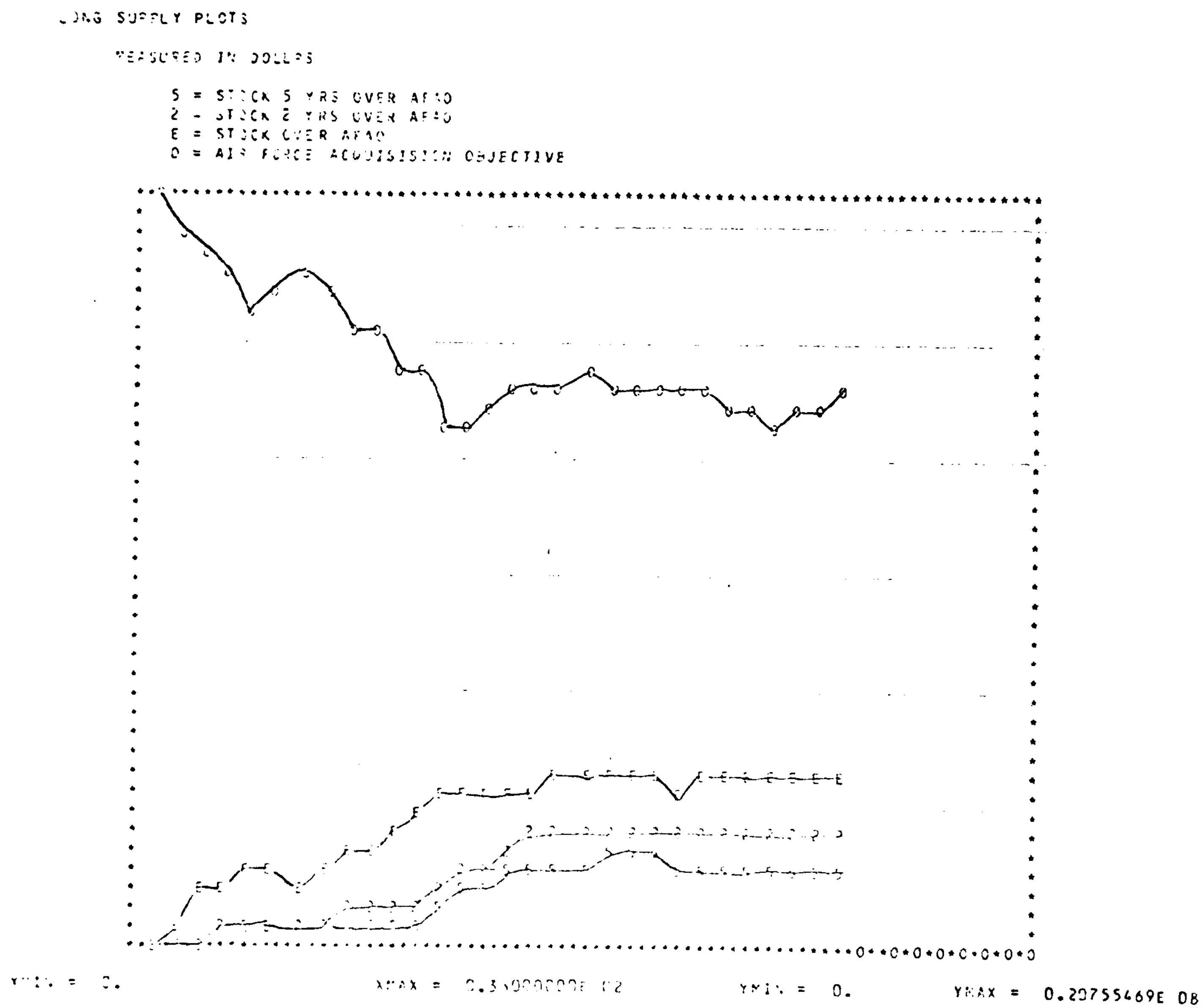


Figure II-10. Dollar Value of Long Supply for Sample OC.H. Policy 1030.

Figure II-10 also plots three measures of the amount of excess stock. In the figure, the "E" denotes the dollar value of stock which is in excess of the AFAO. Similarly, the plot symbol "2" denotes the dollar value of stock which is more than two years of supply in excess of the AFAO, while the symbol "5" denotes the dollar value of stocks which exceed the AFAO plus five years of supply.

Note that the total AFAO drops throughout the 30 quarter interval, while all three measures of excess stock grow continuously.

The general patterns of on-hand and excess stock behavior in Figure II-9 and II-10 are also observed for other inventory management policies. For example, Figures II-11 and II-12 present similar plots of on-hand and excess stock using Run Code 8015. This Run Code corresponds to the use of Policy Code 80 (the exponential error model using a fixed leadtime assumption) and a shortage cost factor of $100. This shortage cost was selected because Run Code 8015 spends an amount of money approximately the same as that spent by Run Code 1030. As shown in Figure II-11, approximately the same general pattern of on-hand and on-order stock activity as was observed for Run Code 1030 is associated with Run Code 8015. Also, Figure II-12 shows Run Code 8015 produces approximately the same general pattern of excess stocks as was observed for Run Code 1030.

Figures II-13 thru II-16 present similar plots of on-hand

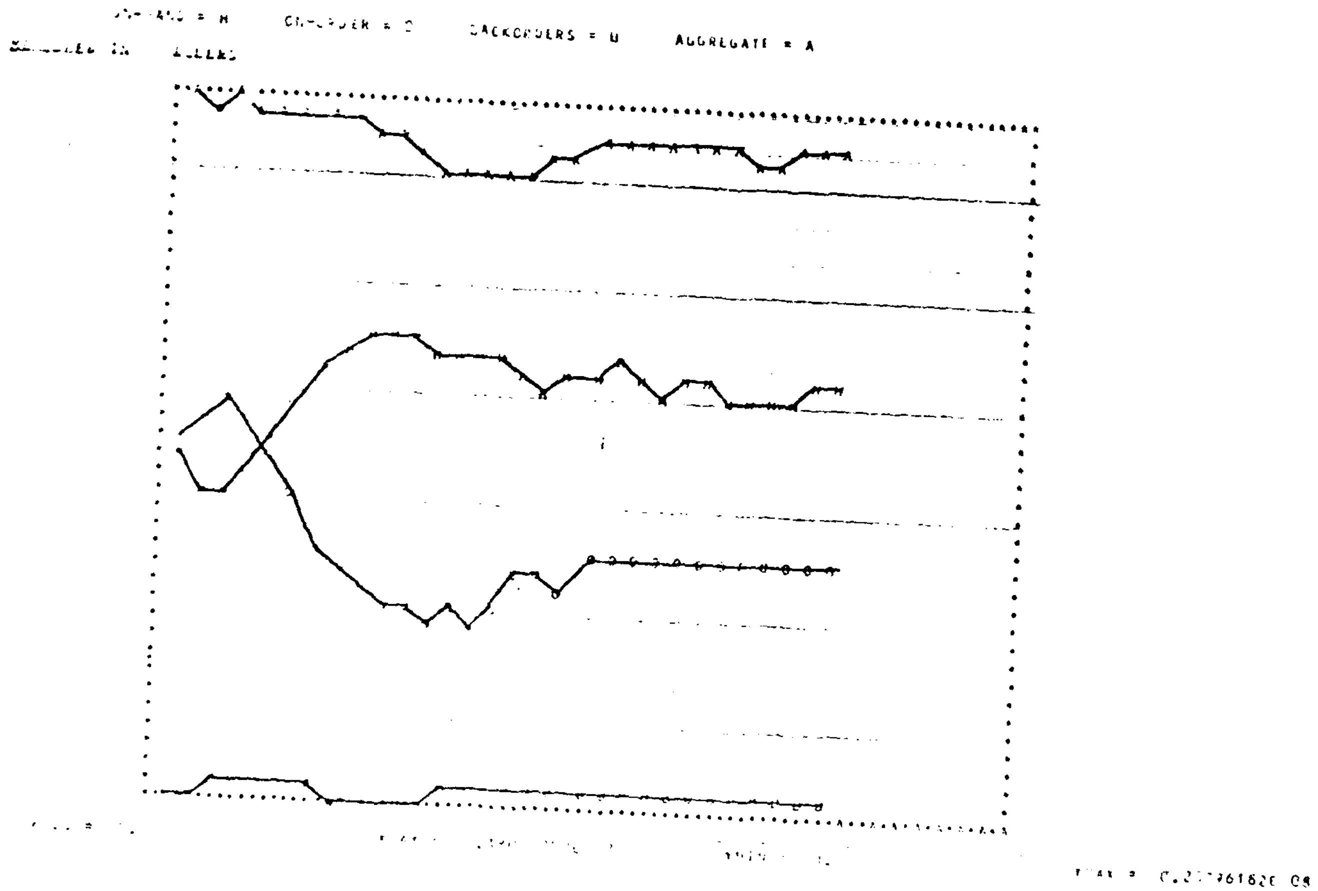


Figure II-11. Dollar Value of On-Hand and On-Order Stocks for Sample OC.H, Policy 8015.

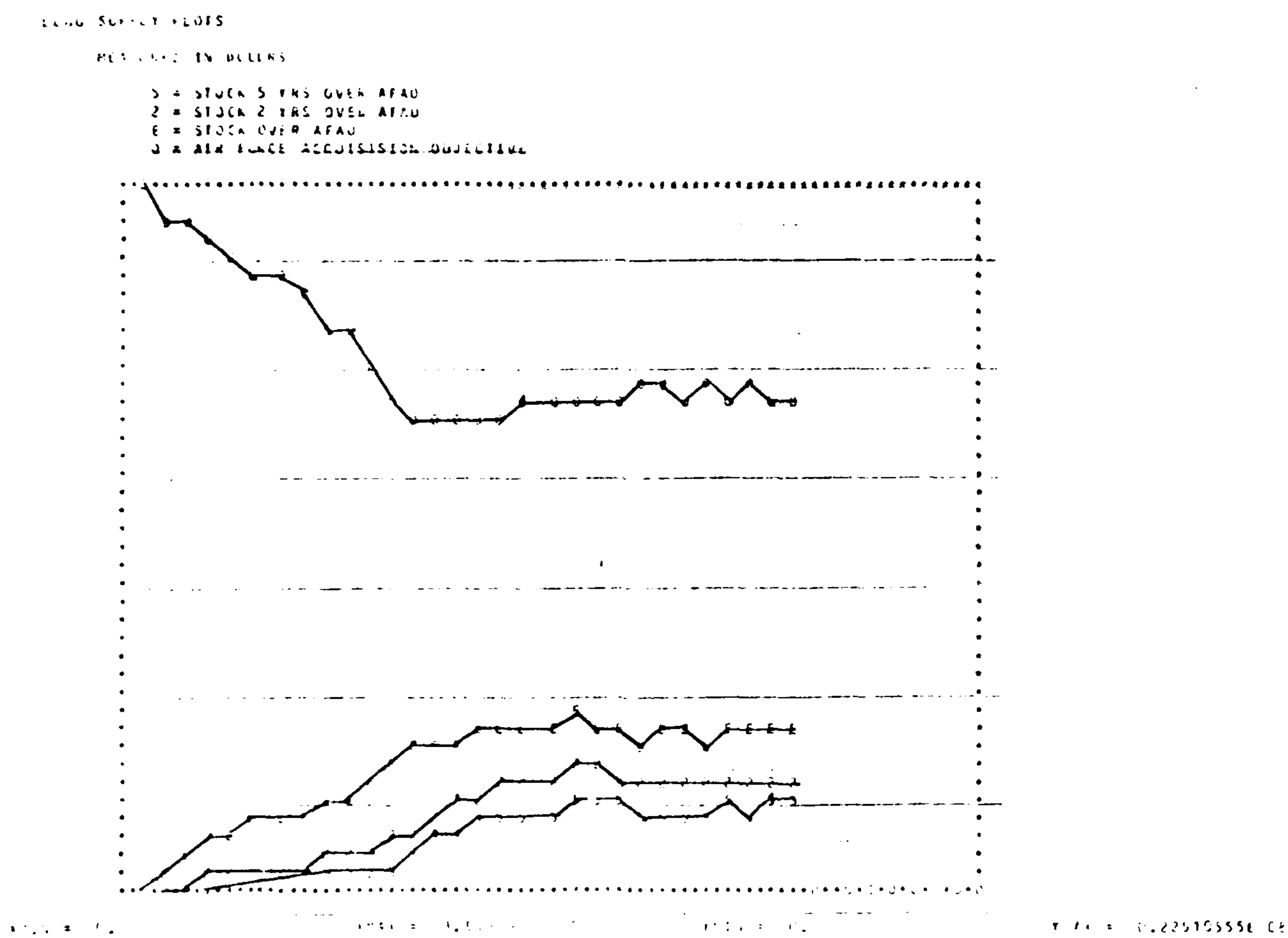


Figure II-12. Dollar Value of Long Supply for Sample OC.H, Policy 8015.

and excess stock for sample SM.H using Run Codes 1030 and 8015, respectively. Note that in this case, too, we observe an initially high level of ordering activity followed by a growth in on-hand stocks. In addition, these runs also show a continuously increasing growth in excess stocks as the time interval progresses. Recall that in Figure II-2, we observed that sample SM.H experiences a significantly declining demand pattern throughout the simulation period. As shown in Figure II-14, this is reflected in a significant drop in the desired stocking objectives during the CY73-79 interval, and a significant increase in excess inventory.

Plots of on-hand and excess stocks for samples SM.L and OC.L are presented in Figures II-17 thru II-24. Note that for these low demand samples, the initial order quantities are very high relative to the average ordering rates observed in later periods. These large initial buys result in a significant increase in on-hand stocks over the levels at which the simulation was initialized. However, note that on-hand stocks tend to increase throughout the simulation for both low activity samples. Also, note that excess stocks grow at a faster proportionate rate for these low activity items than was observed for the high activity item samples. Further, observe that these general observations apply to both the Policy Code 10 and Policy Code 80 runs.

We have discussed plots of only two of the policies which

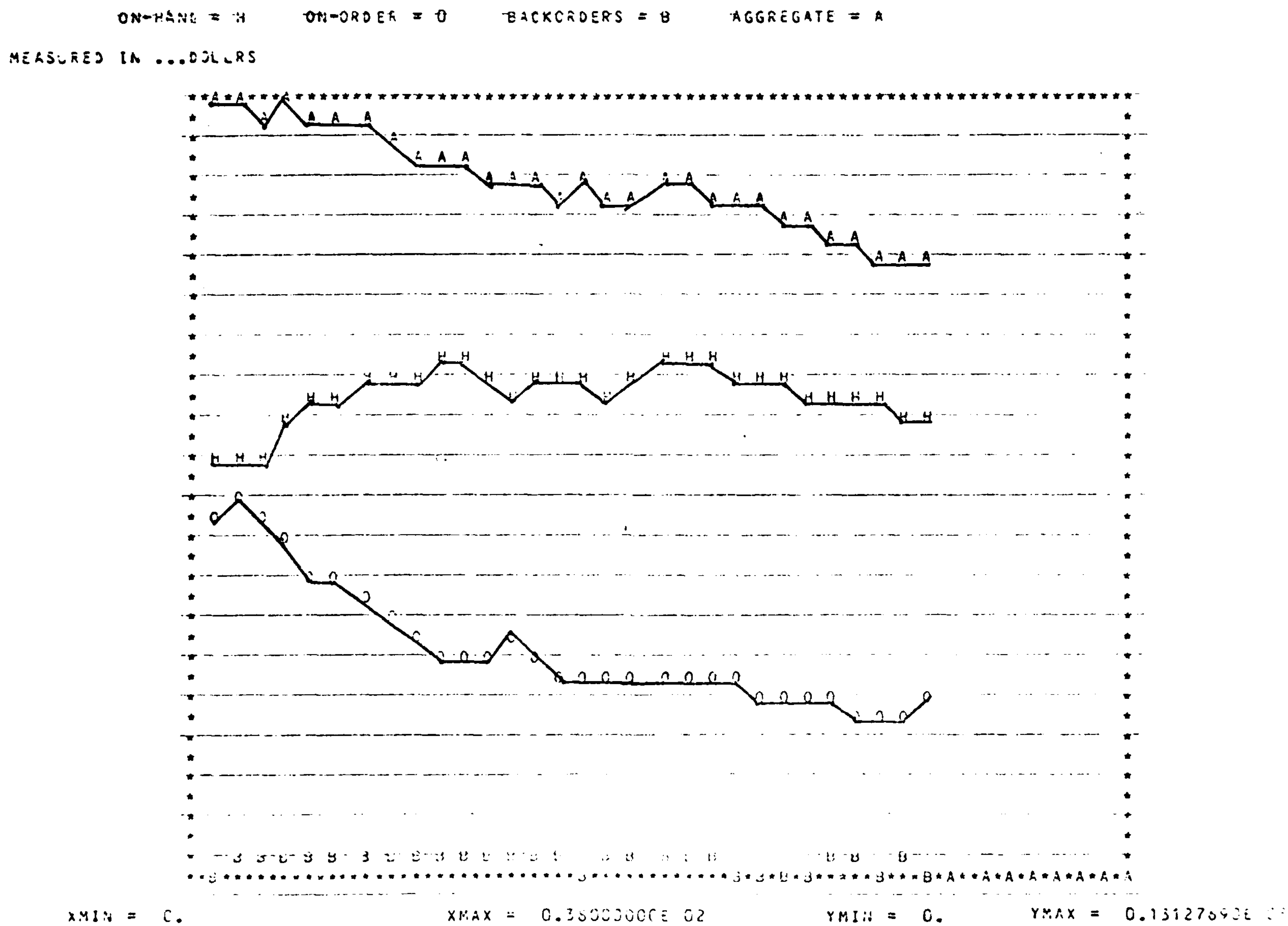
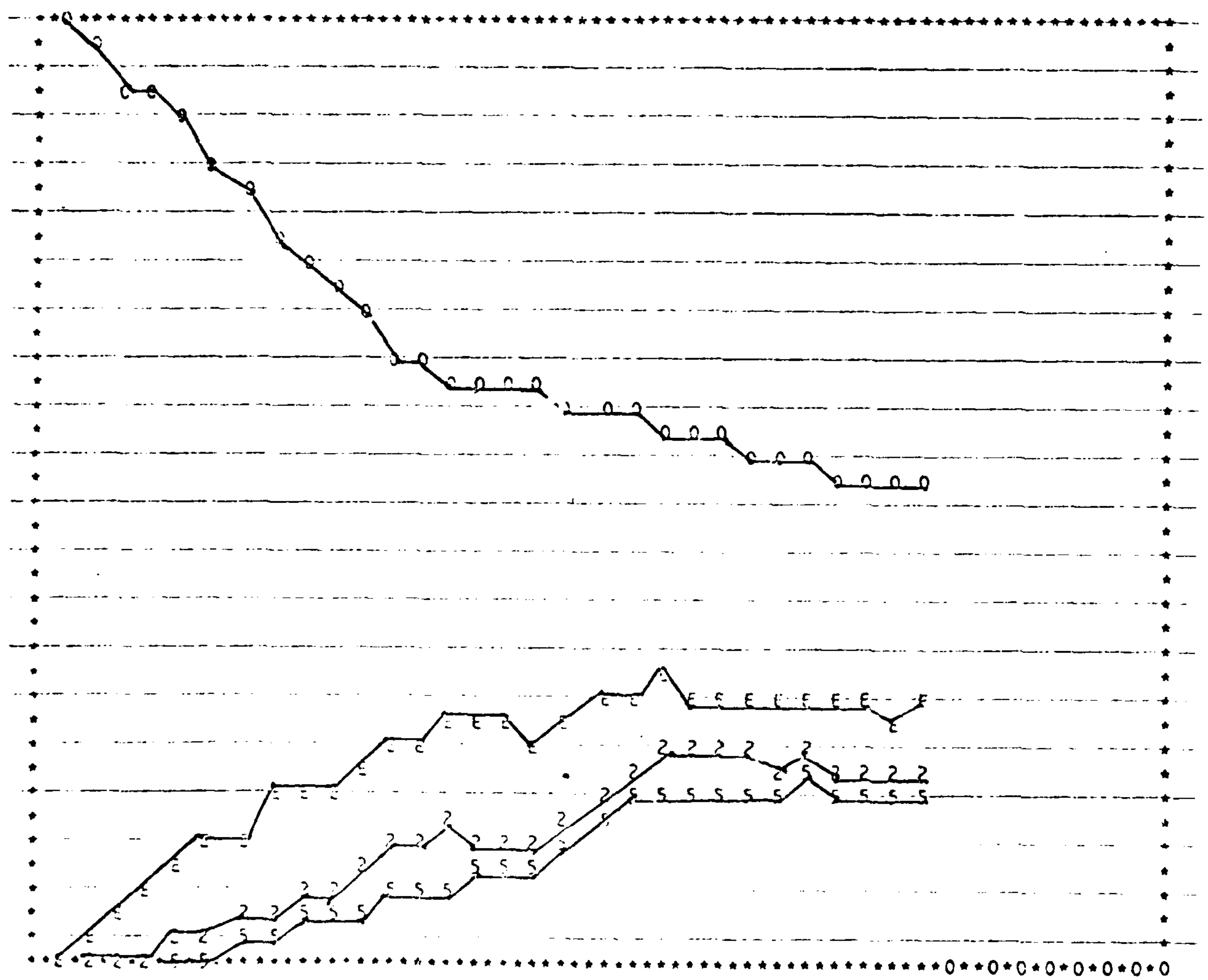


Figure II-13. Dollar Value of On-Hand and On-Order Stocks for Sample SM.H, Policy 1030.

LONG SUPPLY PLOT

MEASURED IN DOLLRS

5 = STOCK 5 YRS OVER AFAO
2 = STOCK 2 YRS OVER AFAO
E = STOCK OVER AFAO
0 = AIR FORCE ACQUISISION OBJECTIVE



XMIN = 0. XMAX = 0.35000000E 02 YMIN = 0. YMAX = 0.14423492E 08

Figure 11-14. Dollar Value of Long Supply for Sample SM.H, Policy 1030.

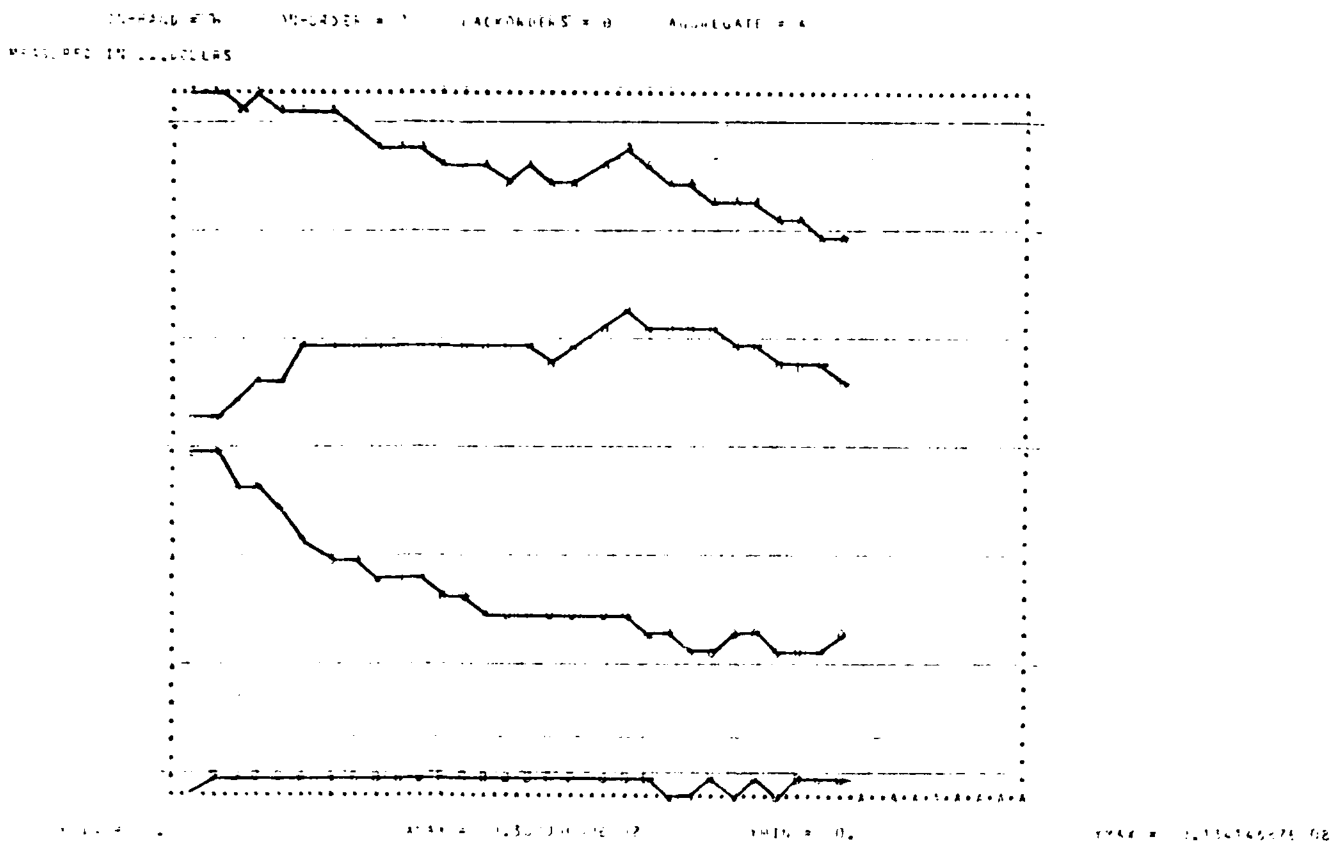


Figure II-15. Dollar Value of On-Hand and On-Order Stocks for Sample SM.H, Policy 8015.

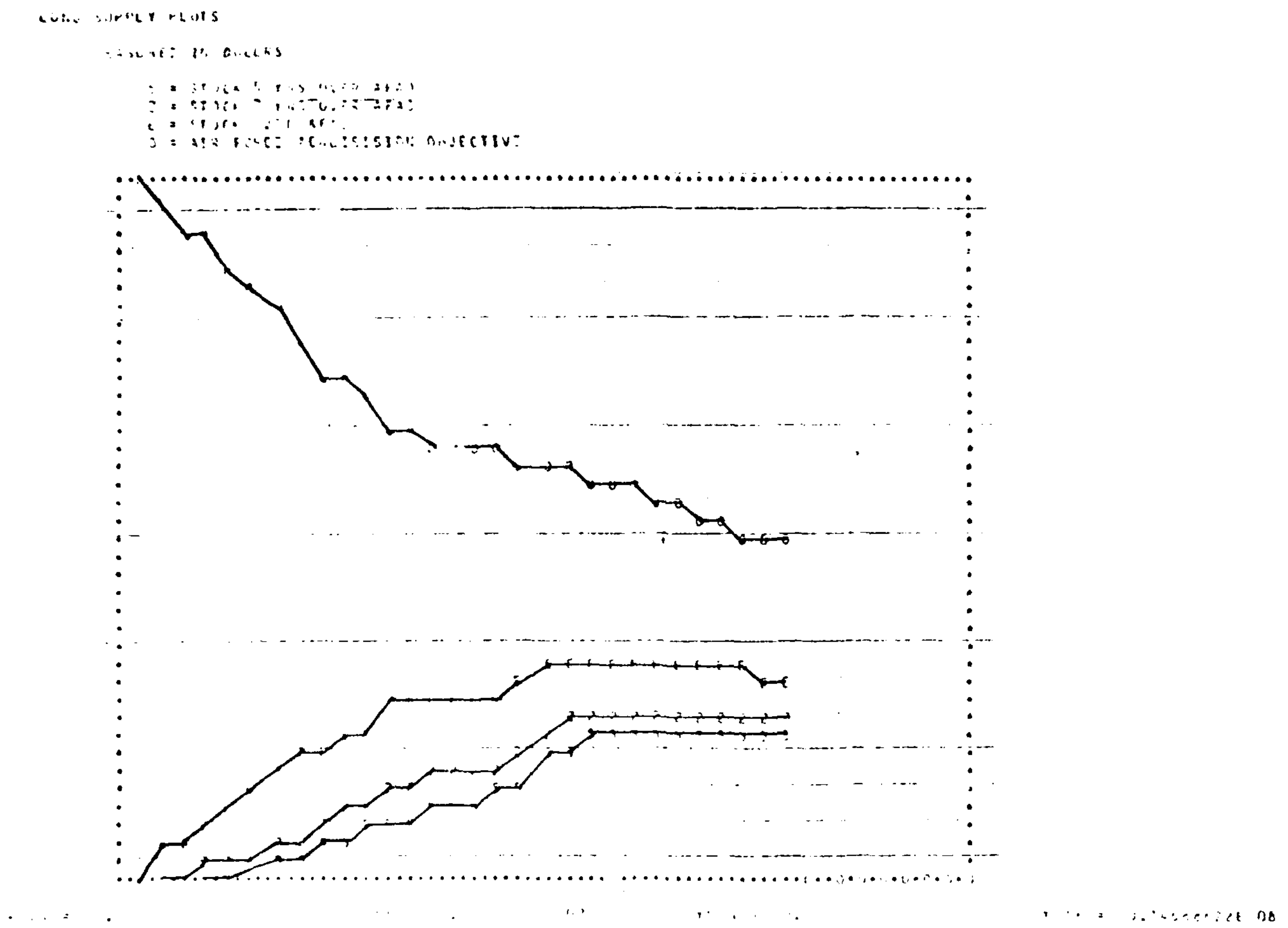


Figure II-16. Dollar Value of Long Supply for Sample SM.H, Policy 8015.

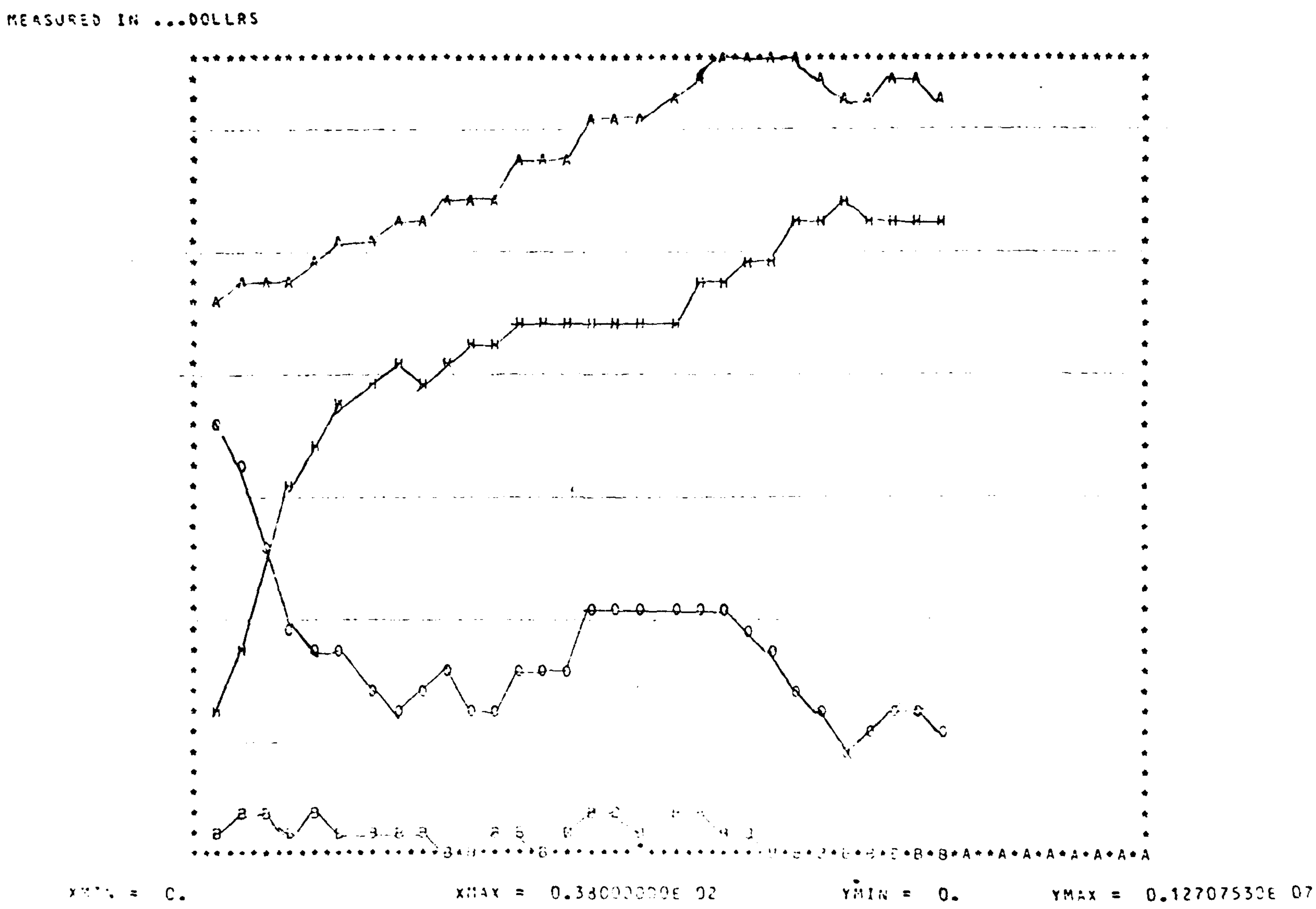
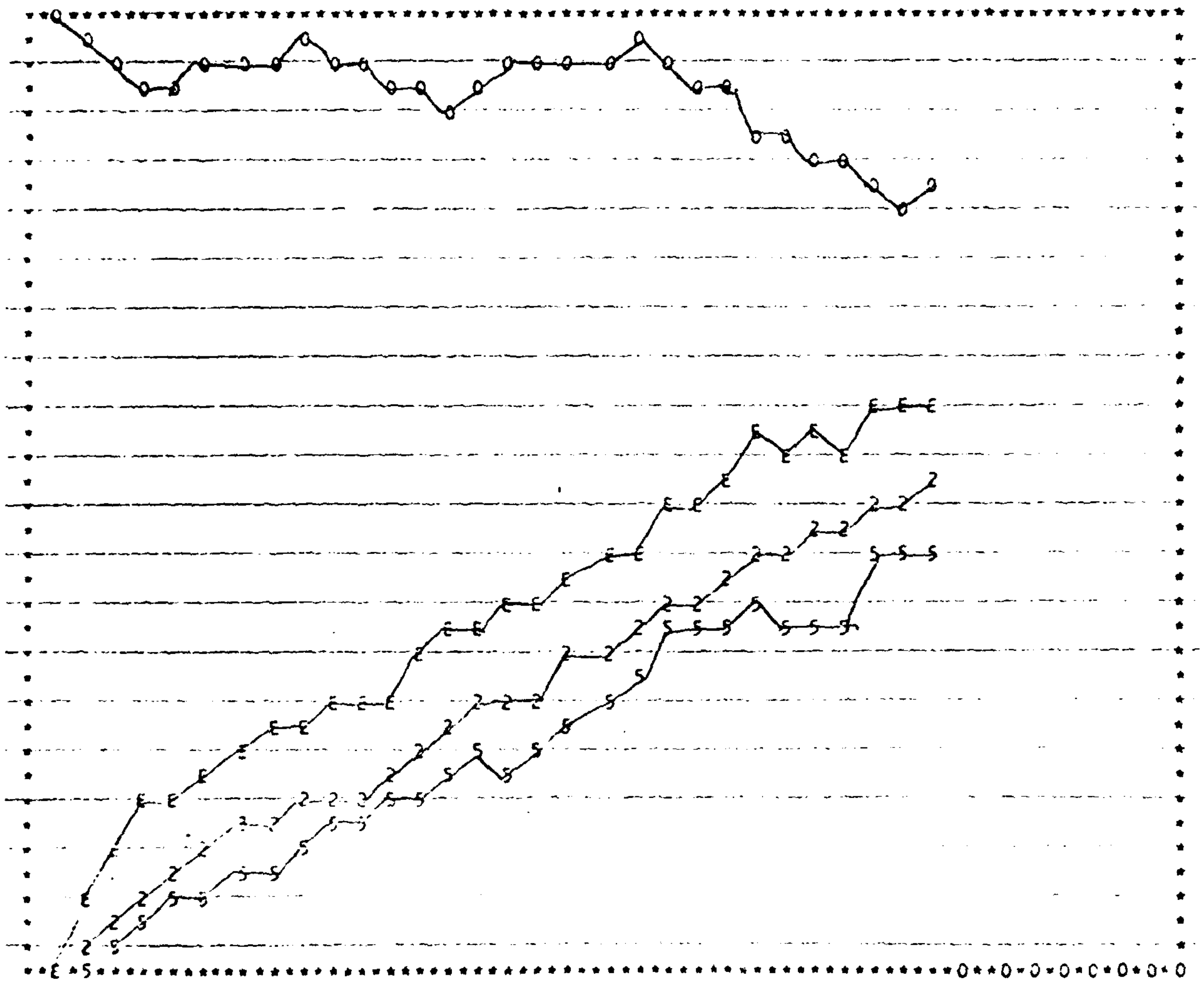


Figure II-17. Dollar Value of On-Hand and On-Order Stocks for Sample OC.L, Policy 1030.

LONG SUPPLY PLOTS

MEASURED IN DOLLRS

S = STOCK 5 YRS OVER AFAO
2 = STOCK 2 YRS OVER AFAO
E = STOCK OVER AFAO
O = AIR FORCE ACQUISISION OBJECTIVE



XMIN = C.   XMAX = 0.32000000E 02   YMIN = 0.   YMAX = 0.945549000E 06

Figure II-18. Dollar Value of Long Supply for Sample OC.L, Policy 1030.

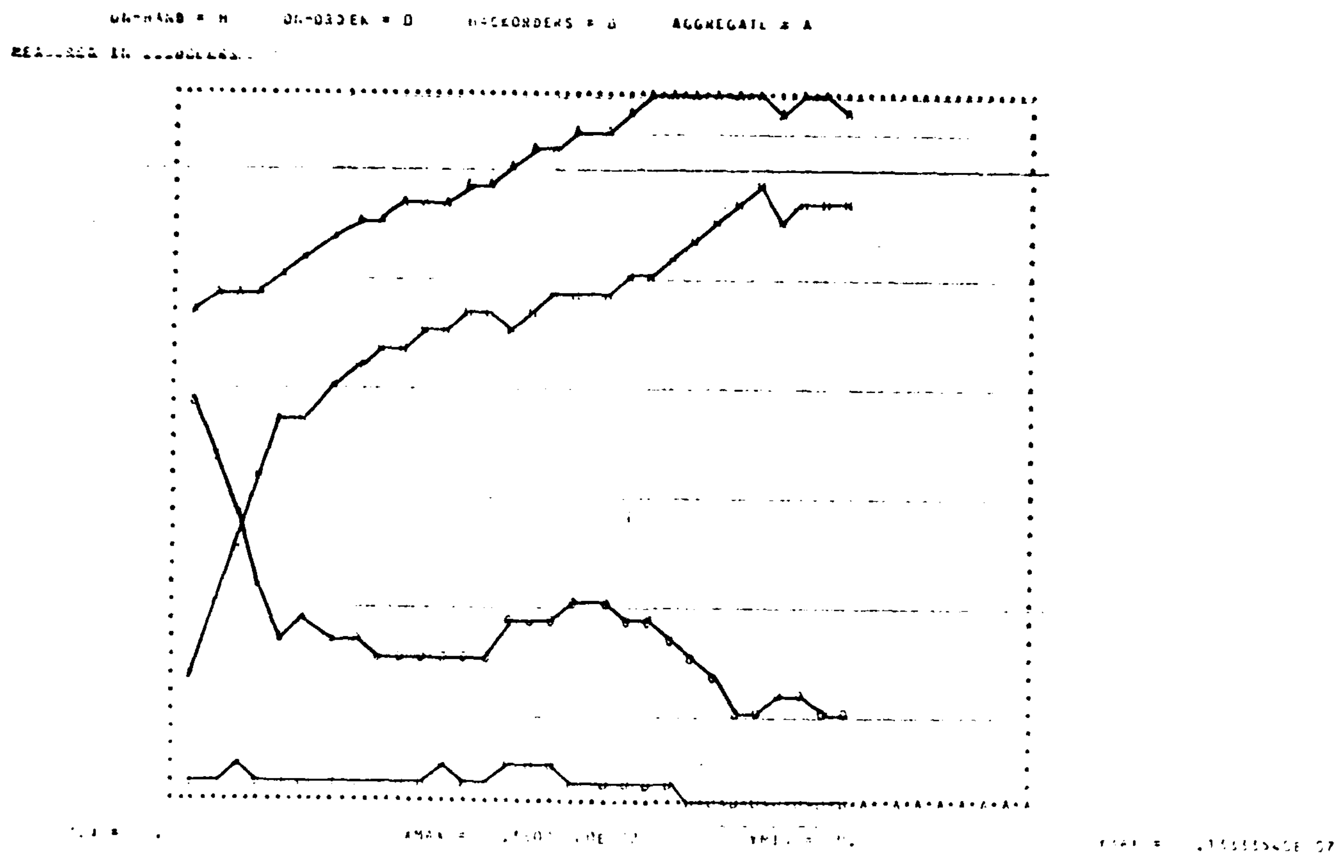


Figure II-19. Dollar Value of On-Hand and On-Order Stocks for Sample OC.L, Policy 8015.

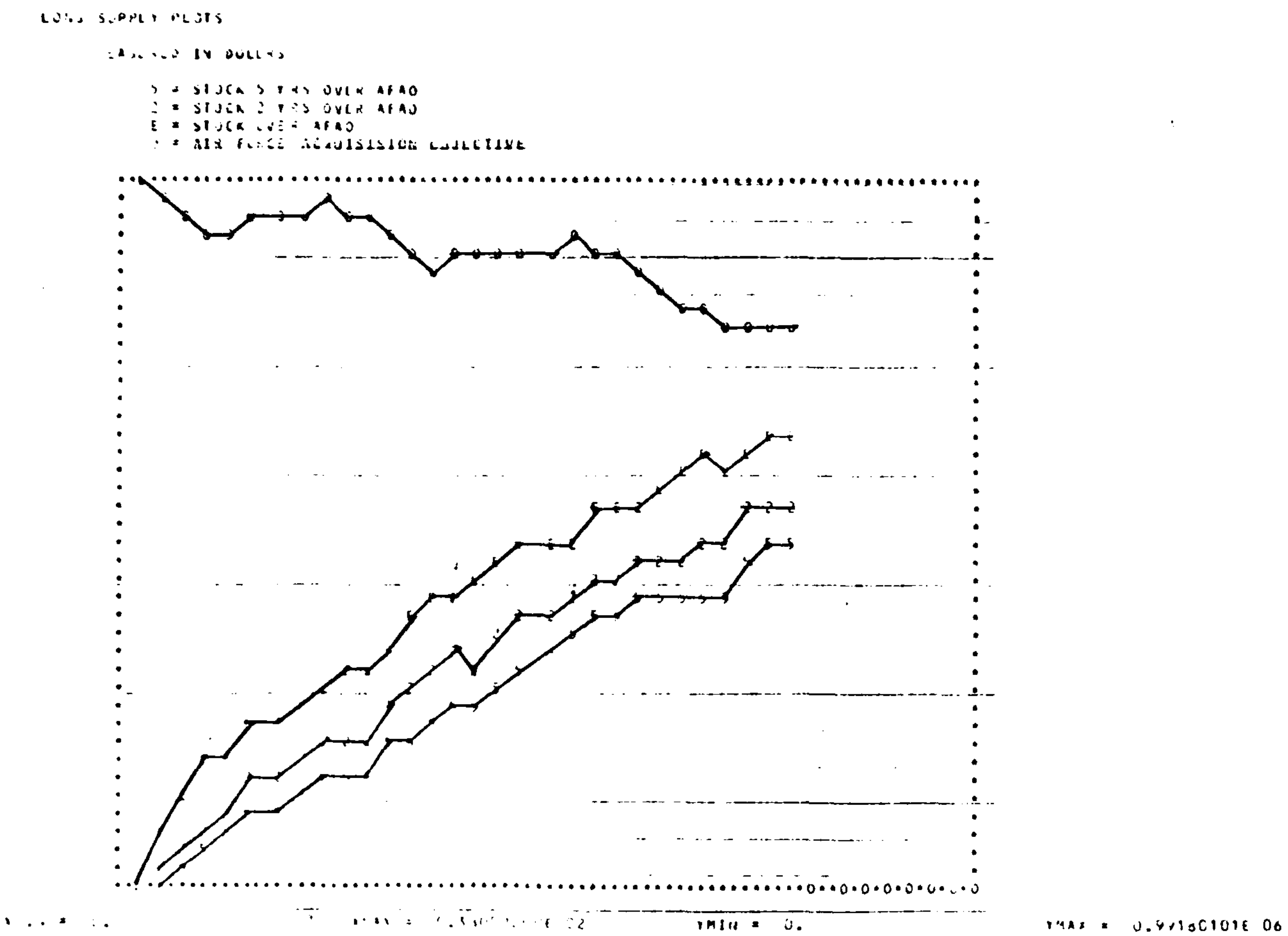


Figure II-20. Dollar Value of Long Supply for Sample OC.L, Policy 8015.

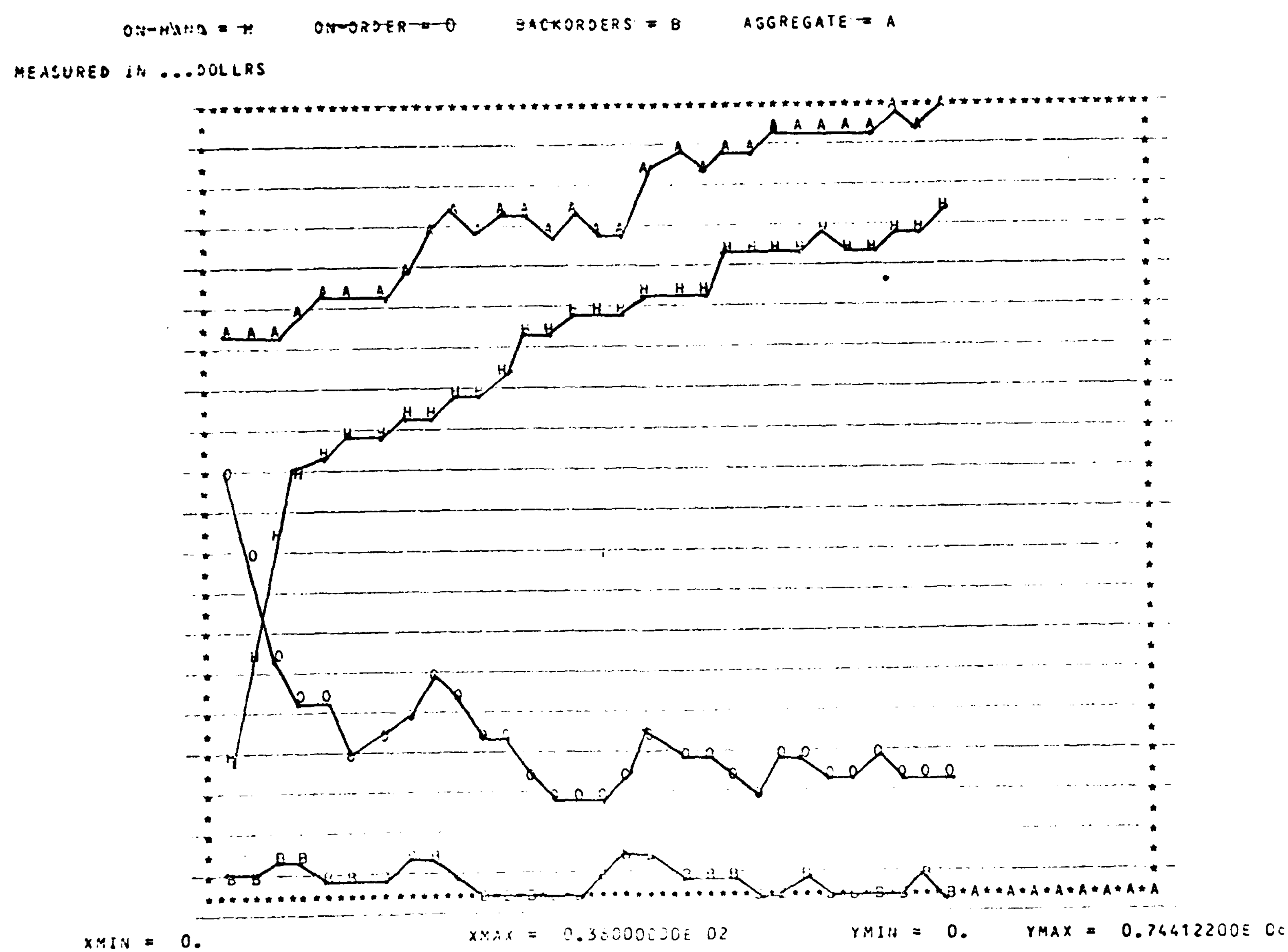
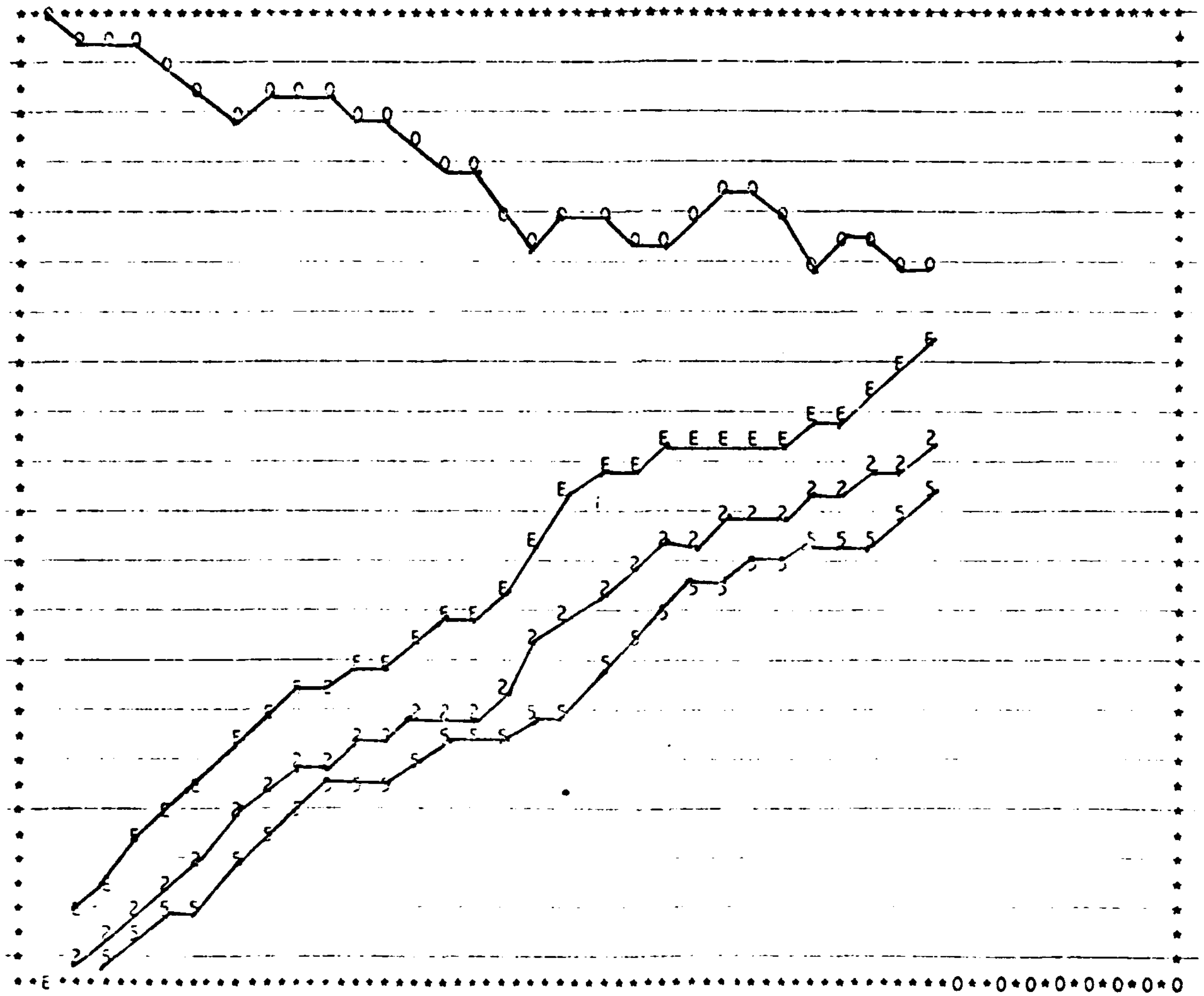


Figure II-21. Dollar Value of On-Hand and On-Order Stocks for Sample SM.L, Policy 1030.

LONG SUPPLY PLOTS

MEASURED IN DOLLRS

S = STOCK 5 YRS OVER AFAO
2 = STOCK 2 YRS OVER AFAO
E = STOCK OVER AFAO
O = AIR FORCE ACQUISITION OBJECTIVE



XMIN = 0. XMAX = 0.38000000E 02 YMIN = 0. YMAX = 0.57246800E 06

Figure II-22. Dollar Value of Long Supply for Sample SM.L, Policy 1030.

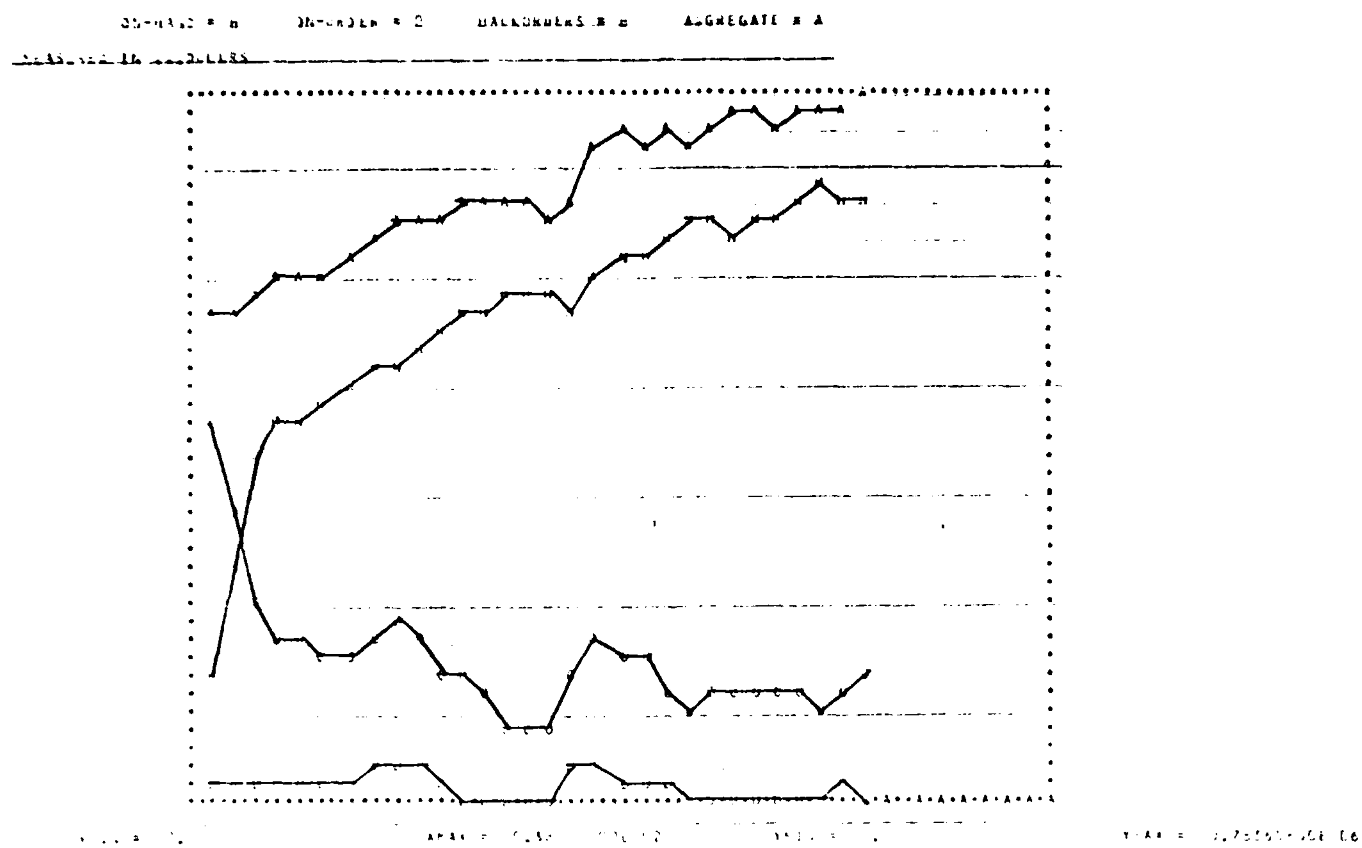


Figure II-23. Dollar Value of On-Hand and On-Order Stocks for Sample SM.L, Policy 8015.

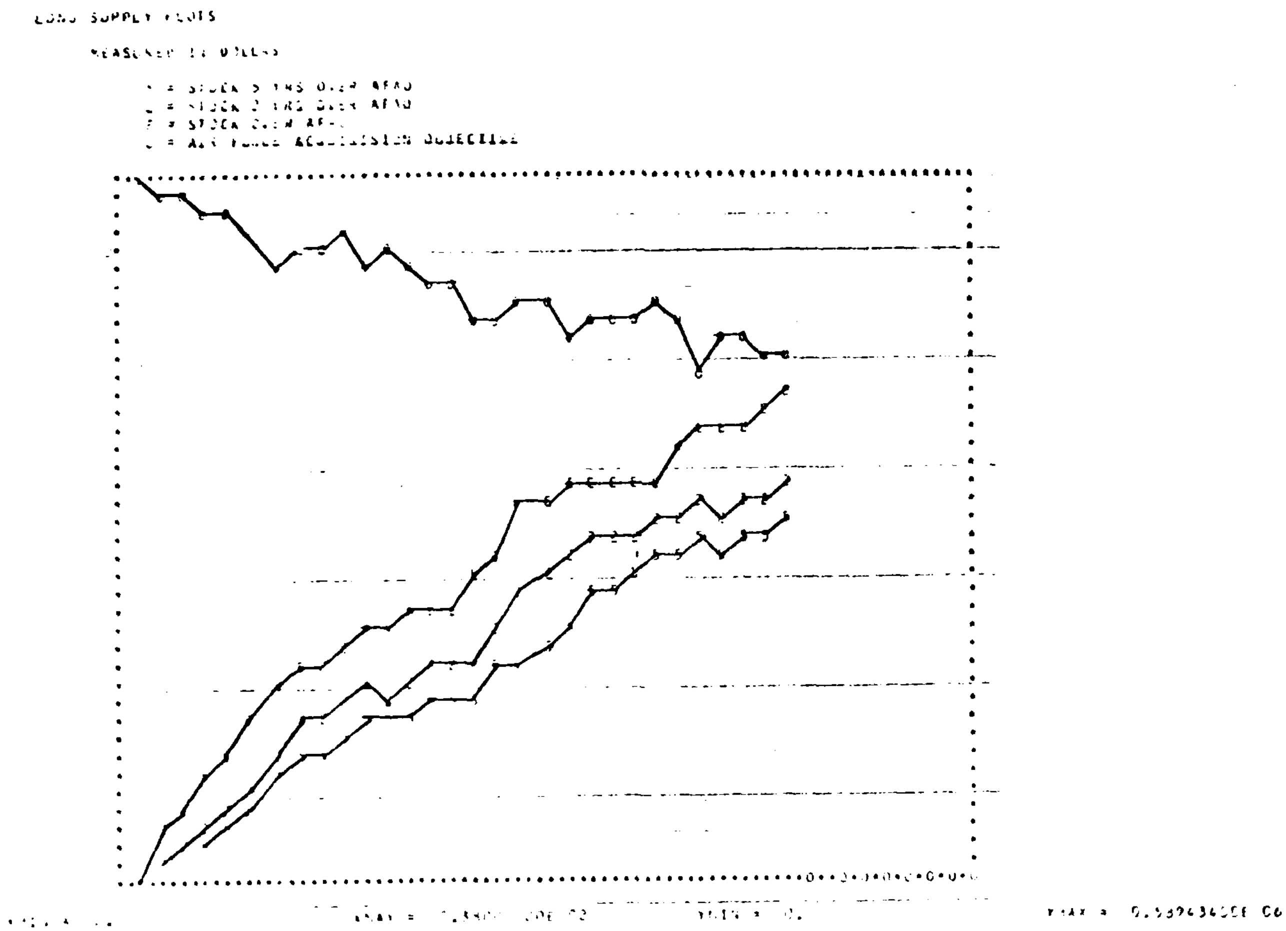


Figure II-24. Dollar Value of Long Supply for Sample SM.L, Policy 8015.

were investigated in this study. However, similar general observations may be found if we look at detailed plots for these other item samples. The general patterns of behavior appear to be dominated by the demand patterns for the individual items, and similar patterns of on-hand and excess stocks are generated under all item policies. However, differences among the item samples do exist. These differences will be discussed in more detail in Sections III and IV.

Section III

INSSIM Sensitivity Measurements

The Inventory System Simulator (INSSIM) is driven by actual Air Force demand histories. The simulation is constructed such that the demand per quarter for a simulated item exactly equals the historical values recorded for that item in D062 history tapes. However, Monte Carlo techniques must be used to determine the priority and size of each individual requisition that is simulated within a quarter, and to determine the precise time of arrival of each requisition within a quarter. In this section, we report results of a series of runs to evaluate the impact of the variability introduced by these Monte Carlo techniques upon overall system performance. We also report results of a pilot study to evaluate the effectiveness of a Inventory Policy Code 20 which deletes "outliers", i.e., Policy Code 20 deletes items which are abnormally large relative to other observed demand values.

The Simulation Scenario

All simulation runs reported in this section used the current D062 inventory management formulas (Policy Code 10) for forecasting and control level calculations. That is, the PT-formulas

were used to compute order quanities and safety stocks for all items, and the computed EOQ and safety level values were then bounded using the same rules as employed in the current D062 system. A detailed description of these rules was presented in Section I. With the exception of Policy 20, all runs use the same forecasting and estimation equations. Policy 20, however, deletes outliers from the moving average estimates of quarterly demand rates. What differed among the runs reported in this section was the combination of factors for which Monte Carlo techniques were used.

Table III-1 presents the parameters utilized for runs reported in this section, as well as the Policy Codes assigned to simplify our discussion of these formulas. Policy Code 10 represents our baseline case. For this Policy Code, resupply lead times were treated as gamma distributed random variables, with a coefficient of variation of .353, and high priority requisitions were generated with a 50% chance. On the other hand, Policy Codes 11 and 12 both treat resupply lead time as a constant. In Policy Code 11 runs, all requisitions were treated as high priority, and consequently an attempt was made to immediately fill each simulated requisition as long as there was stock on hand. On the other hand, Policy Code 12 runs generated both high and low priority requisitions. In this case, there was a 50/50 chance that the requisition was high priority. In this case, if a low priority requisition arrives when on hand stock is less than a 1 month supply, the requisition is back ordered until additional stock becomes available. Policy Code 13 simulated

Table III-1

Parameters for Lead Time and Priority
Sensitivity Analysis Runs

Policy Code	Shortage Cost Factor	Percent High Priority Requisitions	Resupply Lead Time	Management Formulas
10	500	50%	Random	Current
11	500	100%	Constant	Current
12	500	50%	Constant	Current
13	500	100%	Random	Current
20	500	50%	Random	Current, with outliers excluded

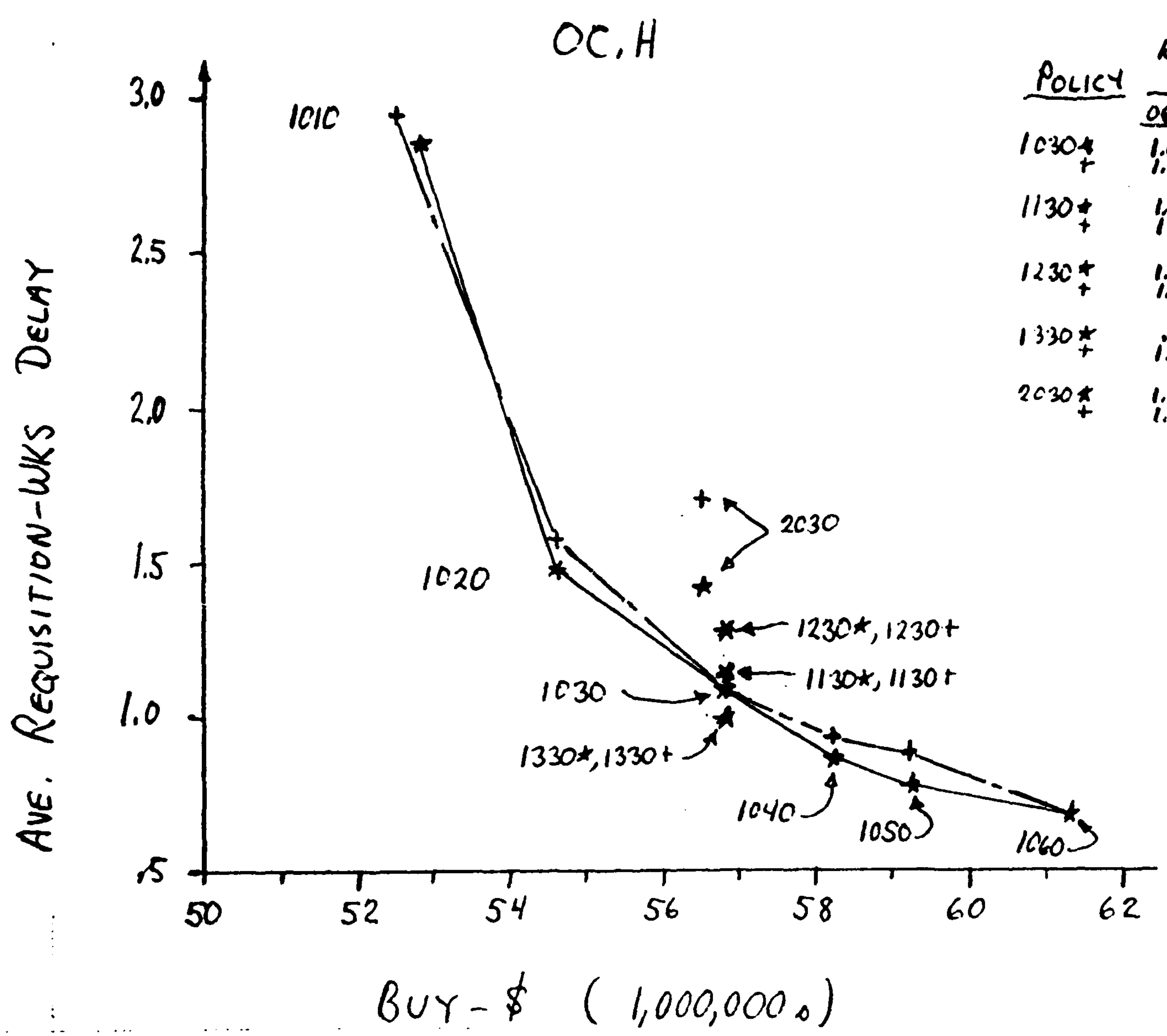
the situation in which resupply lead time was gamma distributed, and all requisitions were high priority. Finally, as discussed above, Policy Code 20 runs were identical to Policy Code 10 runs with the exception that outliers were excluded from demand rate calculations. Precise rules used in Policy Code 20 calculations are discussed in Section I.

We performed twelve simulation runs using Policy Code 10 for each of the four item samples. In six of these twelve runs, the requisition generation process was controlled so that exactly the same stream of requisitions--with each requisition arriving at the same simulated instant and involving the same number of units--was used in each simulation run. These six runs used implied shortage cost factors of .1,250, 500, 750, 1000, and 2000, respectively. Hence, these six runs illustrate how policy code 10 would have performed under differing funding levels dealing with exactly the same requisition stream. We also used the same sequence of support level values for six additional Policy Code 10 runs for each item sample. In this second sequence of six runs, the size and timing of requisitions within a given quarter was allowed to vary from run to run. However, as in all INSSIM runs, for a given item exactly the same total number of units, with the same total dollar value, was simulated each quarter in each of these runs. Thus, a comparison of the results of the two sequencies of twelve runs gives an indication of the impact of variability of requisition sizes and of timing within a given quarter upon the variability of simulation results.

Policy Codes 11, 12, 13, and 20 were each ran under two different requisition streams. In one of these runs, which we denote by a "*", we used exactly the same sequence of requisition as described for Policy Code 10 above. In the second of these runs, the size and timing of individual requisitions within a quarter was allowed to vary. We use a "+" to denote runs in the second catagory. In all of these runs for policy codes 11, 12, 13, and 20, we used an implied shortage cost of $500.00.

Figures III-1 thru III-8 illustrate our results. Figures III-1 thru III-4 plot the observed average requisition weeks delay verses the corresponding total simulated 30-quarter procurement expenditures. The curves are for samples OC.H, SM.H, OC.L, and SM.L respectively. On the other hand, Figures III-5 thru III-8 plot requisition fill rate verses Buy Dollar curves for each of these samples. As noted above, points marked by "*" represent simulation runs which had exactly the same requisition stream as all other "*" runs. On the other hand, points marked by a "+" may represent a different requisition stream from run to run. Again, however, exactly the same number of units per quarter were simulated for each sampled item in every run in which that item was involved.

In Figure III-1, the lines connect points representing the observed average requisition weeks of delay and corresponding Buy Dollars using Policy Code 10 under several different funding levels. These provide a frame work of comparison with the individual points representing Policy Code 11, 12, 13, and



POLICY	AVE REQ-WKS DELAY OBS	AVE REQ-WKS DELAY AVE	BUY-$ OBS	BUY-$ AVE
1030*	1.09	1.10	56.8	[illegible]
+	1.10		56.8	
1130*	1.13	1.15	56.8	[illegible]
+	1.16		56.7	
1230*	1.28	1.28	56.8	[illegible]
+	1.28		56.7	
1330*	.99	1.00	56.8	[illegible]
+	1.00		56.8	
2030*	1.42	1.56	56.5	[illegible]
+	1.70		56.5	

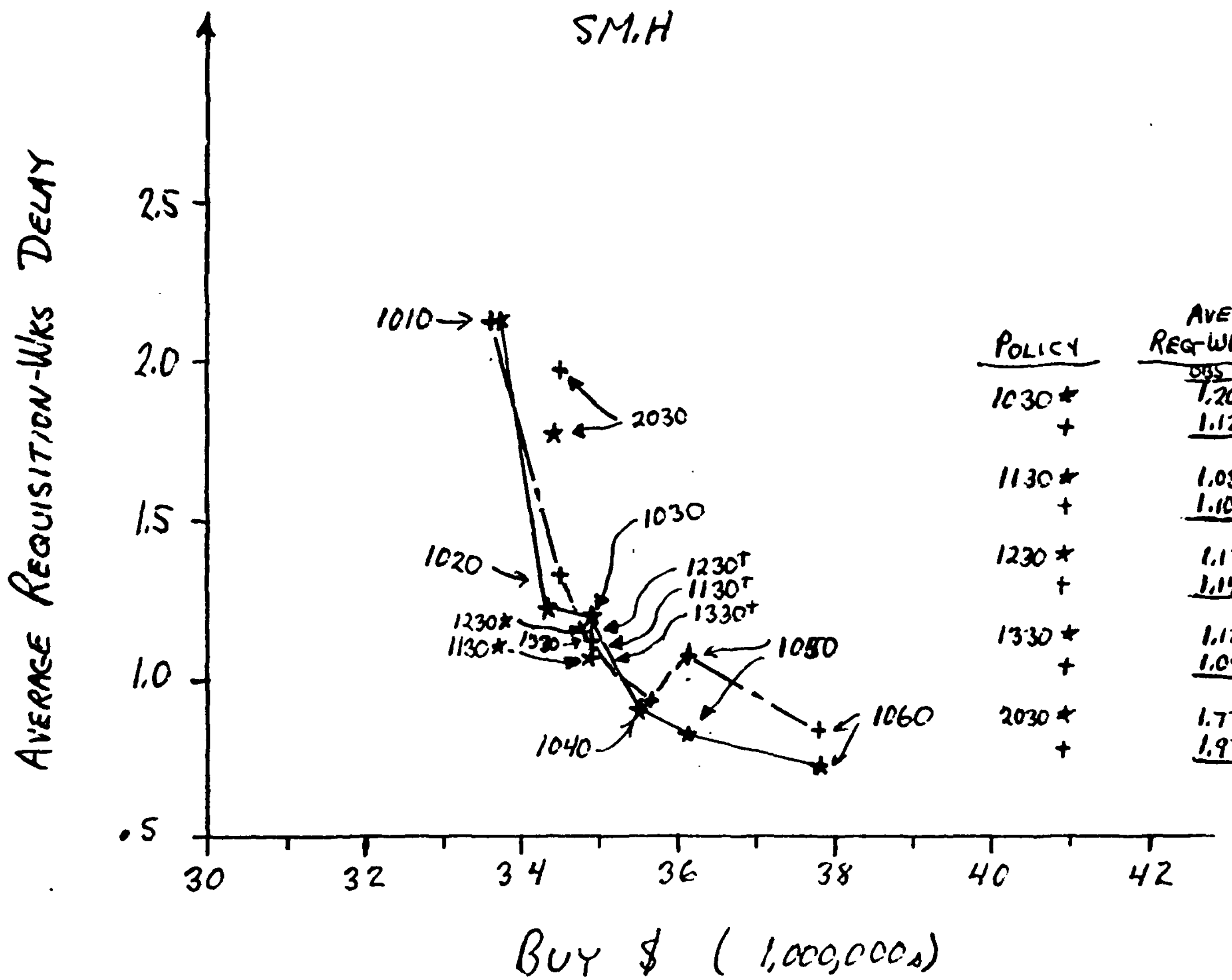
III-1. OC.H Observrved Requisition-Weeks vs Buy Dollars.

20 results. Note that the both "*" and "+" for Policy Code 20 points are significantly above and to the right of these baseline curves. This indicates that these Policy Code 20 results are significantly less cost effective than values which were achieved using Policy Code 10. Note that the curve for Policy Code 10 also dominated the points for Policy Codes 11 and 12, but that Policy Code 13 fell below the Policy Code 10 cost effectiveness curve.

Figure III-2 presents similar requisition delay versus Buy Dollar results for the sample SM.H. In this sample, average requisition weeks of delay was a more erratic statistic and the curves jump around significantly. For this data set, policy code 20 also performs very badly relatively to the Policy Code 10 curve. On the other hand, it is difficult to distinguish between Policy Code 10 results and the results for Policy Codes 11, 12, and 13.

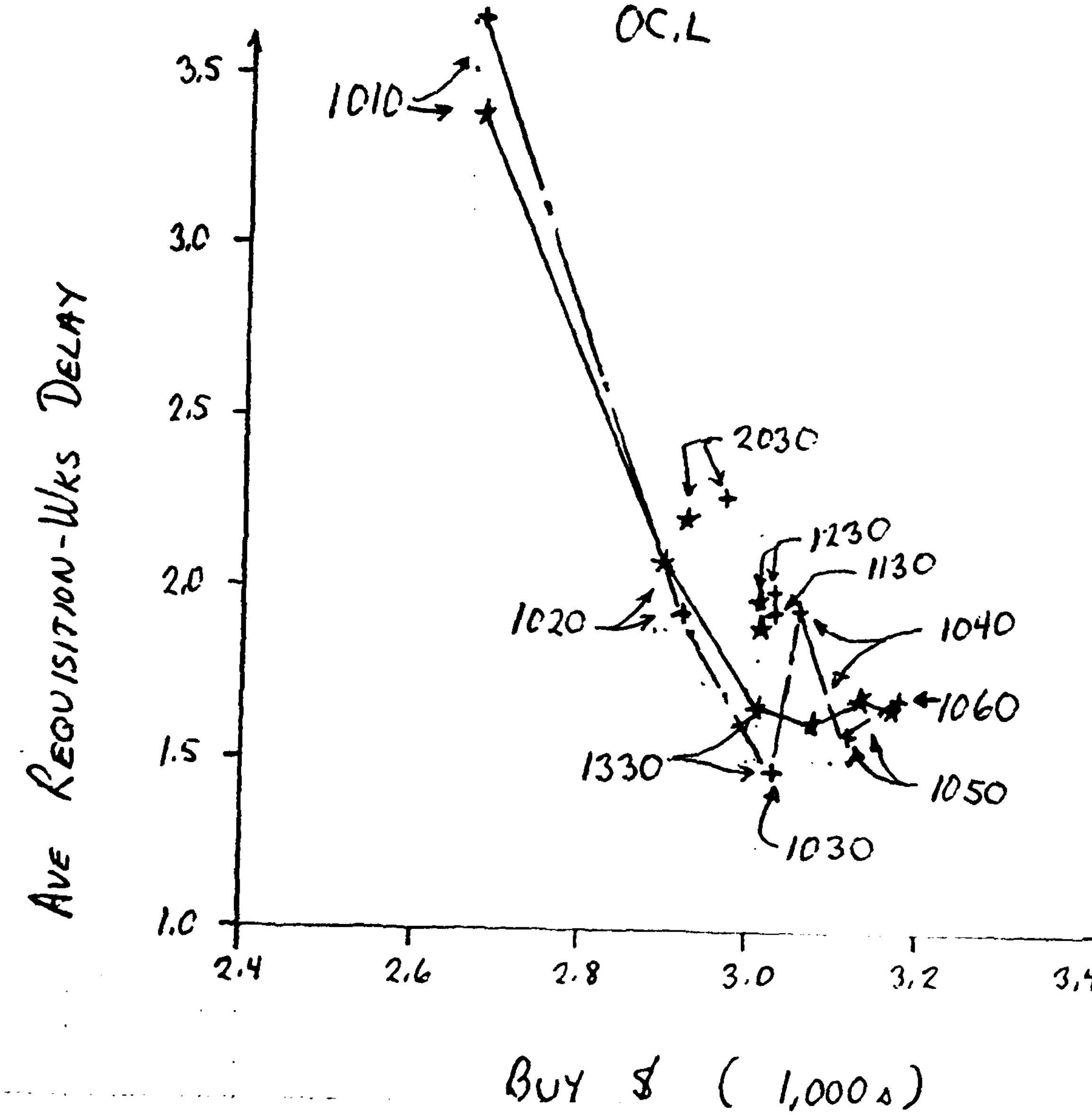
The results for samples in OC.L and SM.L are presented in Figures III-3 and III-4. In these figures Policy Code 20 also performs quite badly, and the results for Policy Code 11 and 12 are also dominated by the Policy Code 10 results.

Figures III-5 thru III-8 present the observed requisition fill rate verses Buy Dollar cuves for each of the four item samples. In this case, an ideal point would lie to the left and above other points on the graph, i.e., an ideal policy would spend



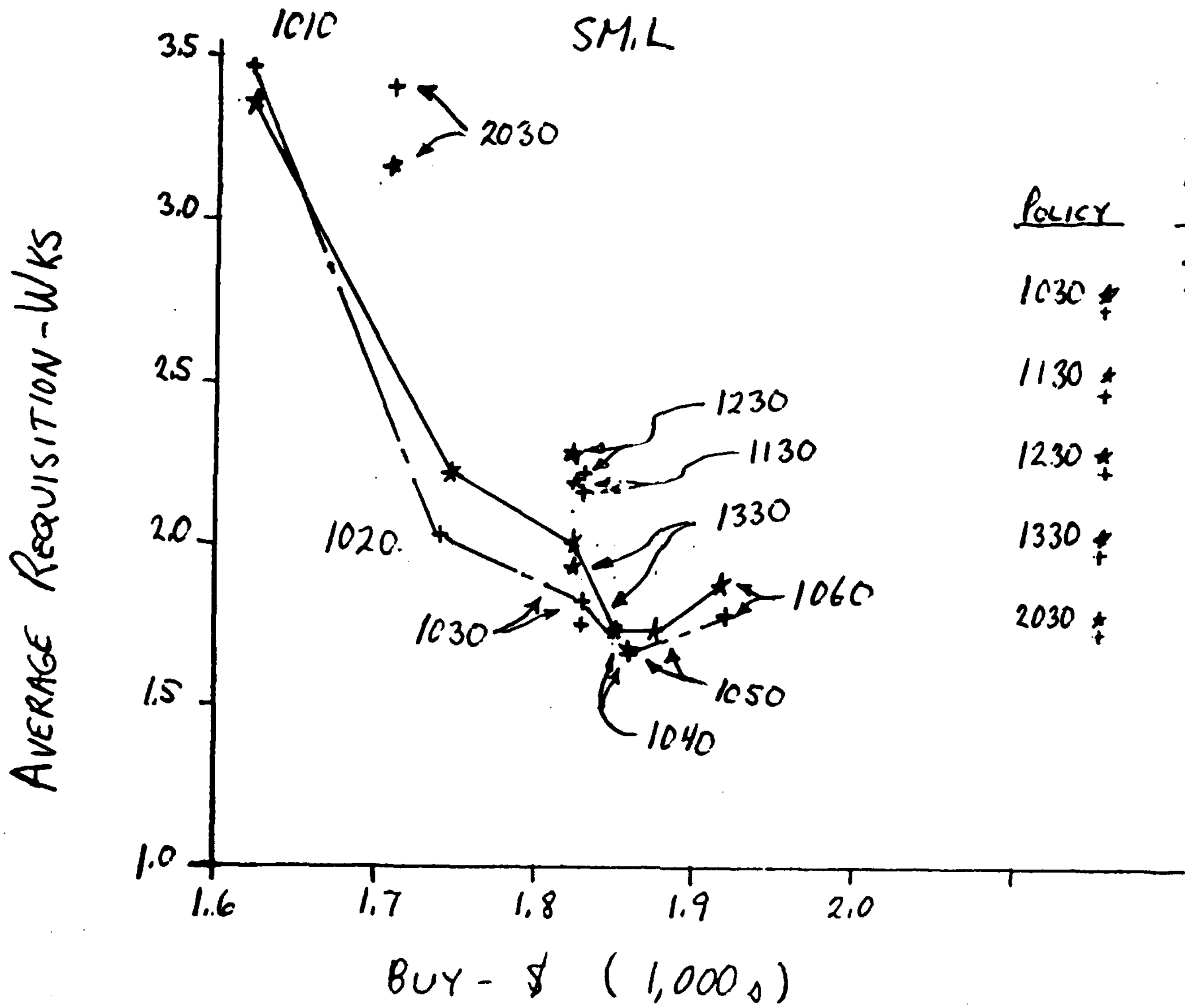
Policy	Ave Req-Wks OBS	Ave Req-Wks AVE	Buy $ OBS	Buy $ AVE
1030 ★	1.20		34.9	
+	1.12	1.16	34.9	[illegible]
1130 ★	1.08		34.9	
+	1.10	1.09	34.9	[illegible]
1230 ★	1.17		34.9	
+	1.14	1.15	34.9	[illegible]
1330 ★	1.12		34.9	
+	1.04	1.08	34.9	[illegible]
2030 ★	1.77		34.4	
+	1.97	1.87	34.5	[illegible]

III-2. SM.H Obserrved Requisition-Weeks vs Buy Dollars.



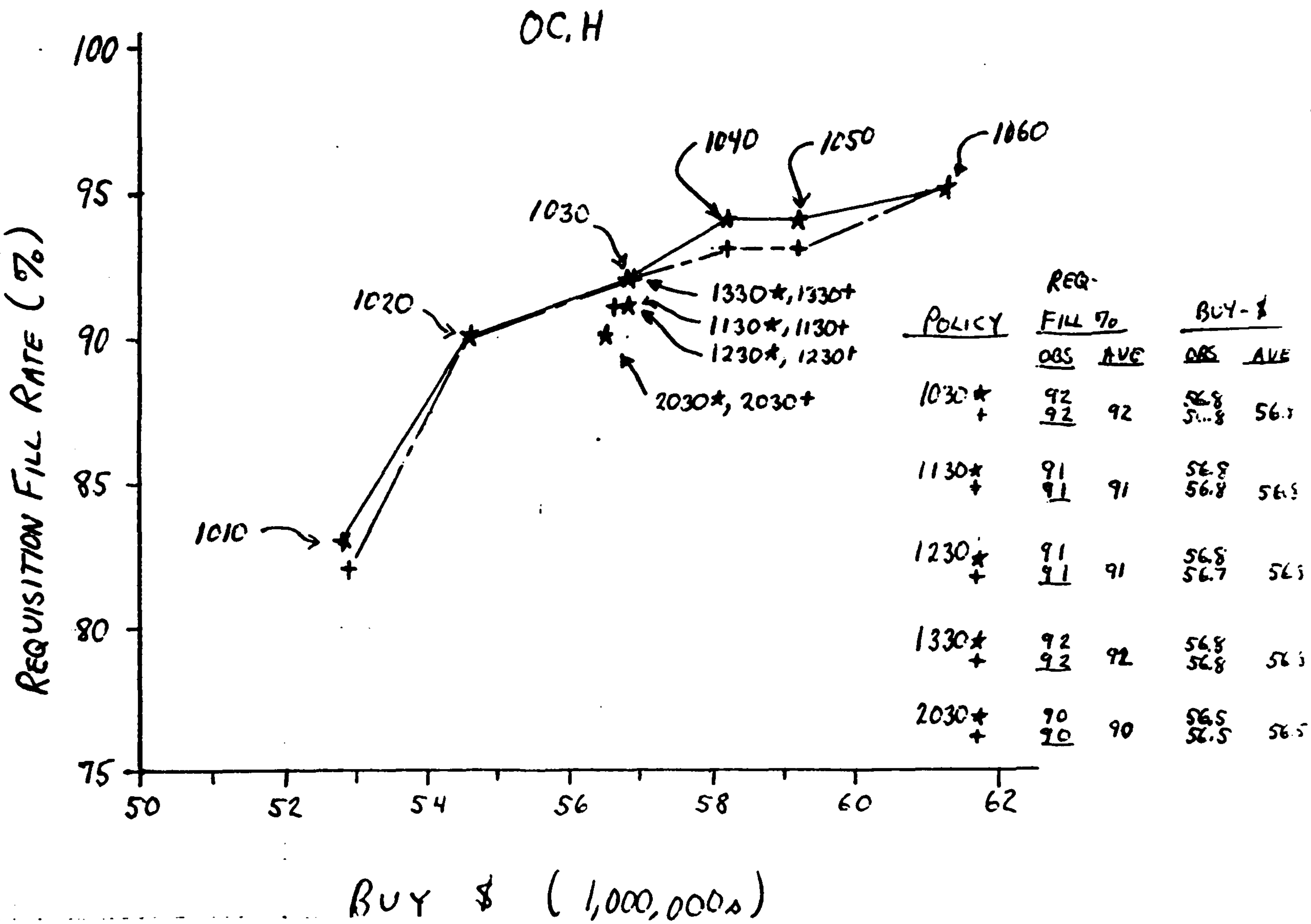
Policy		Ave Req-Wks Delay OBS	Ave Req-Wks Delay AVE	Buy-$ OBS	Buy-$ AVE
1030	★	1.65	1.56	3011	3021
	+	1.47		3030	
1130	★	1.89	1.91	3011	3021
	+	1.93		3030	
1230	★	1.96	1.97	3011	302[illegible]
	+	1.97		3030	
1330	★	1.59	1.53	3011	302[illegible]
	+	1.47		3030	
2030	★	2.20	2.27	2938	295[illegible]
	+	2.34		2970	

III-3. OC.L Obserrved Requisition-Weeks vs Buy Dollars.



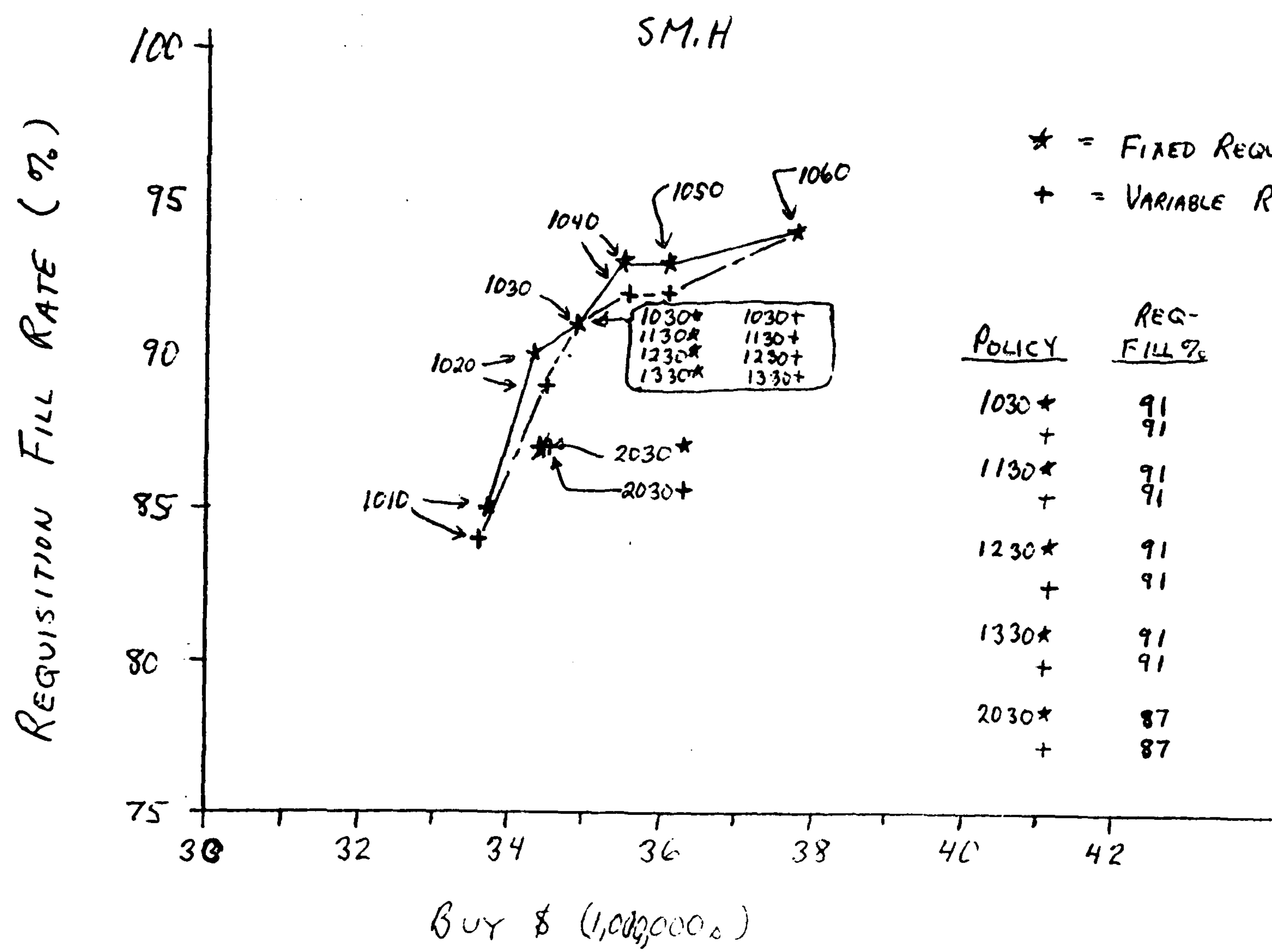
POLICY	AVE REQ-WKS DELAY OBS	AVE REQ-WKS DELAY AVE	BUY-$ OBS	BUY-$ AVE
1030 ✱ +	2.00 1.82	1.91	1822 1830	1826
1130 ✱ +	2.19 2.16	2.18	1822 1830	1826
1230 ✱ +	2.27 2.21	2.24	1822 1830	1826
1330 ✱ +	1.94 1.76	1.85	1822 1830	1826
2030 ✱ +	3.18 3.41	3.30	1709 1718	1716

III-4. SM.L Obserrved Requisition-Weeks vs Buy Dollars.



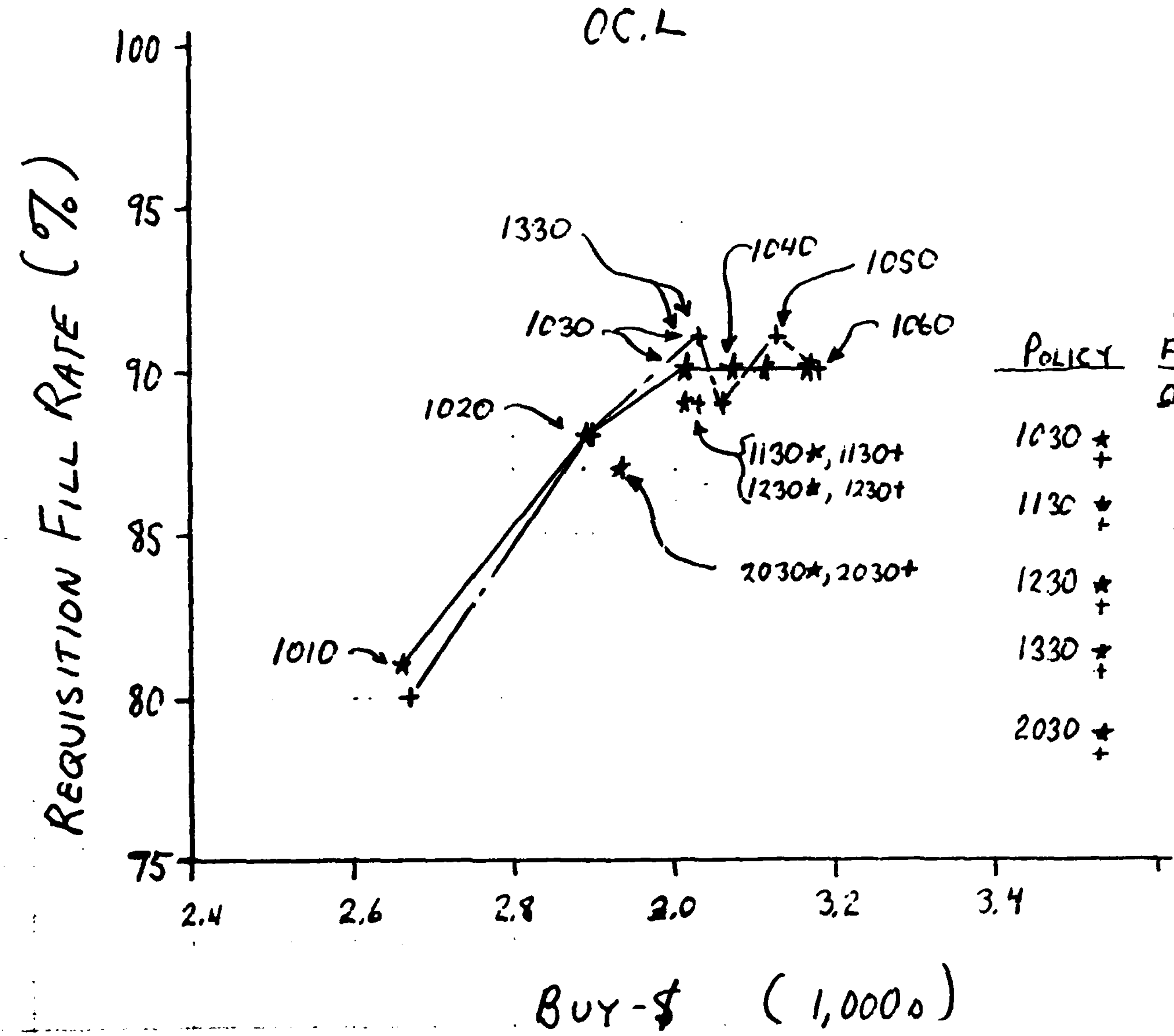
POLICY	REQ-FILL % OBS	REQ-FILL % AVE	BUY-$ OBS	BUY-$ AVE
1030★	92	92	56.8	56.[illegible]
+	92		5[illegible]8	
1130★	91	91	56.8	56.[illegible]
+	91		56.8	
1230★	91	91	56.8	56.[illegible]
+	91		56.7	
1330★	92	92	56.8	56.[illegible]
+	93		56.8	
2030★	90	90	56.5	56.5
+	90		56.5	

III-5. OC.H Observrved Fill Rate vs Buy Dollars.



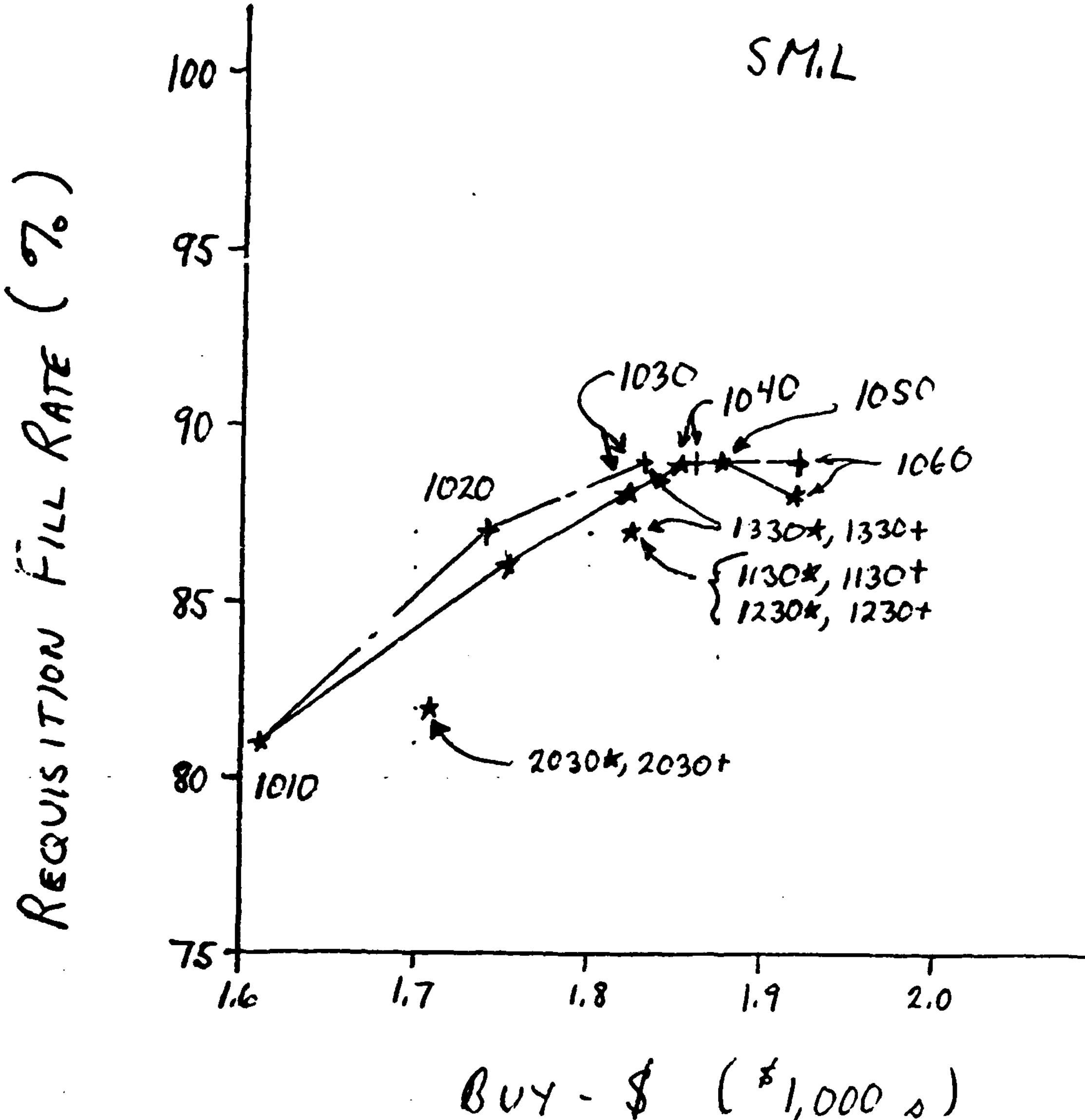
POLICY	REQ-FILL %	BUY-$
1030★	91	34.9
+	91	34.9
1130★	91	34.9
+	91	34.9
1230★	91	34.9
+	91	34.9
1330★	91	34.9
+	91	34.9
2030★	87	34.4
+	87	34.5

III-6. SM.H Obserrved Fill Rate vs Buy Dollars.



Policy		Req. Fill % OBS	Req. Fill % AVE	Buy-$ OBS	Buy-$ AVE
1030	★	90		3011	
	+	91	91	3030	3020
1130	★	89		3011	
	+	89	89	3030	3020
1230	★	89		3011	
	+	89	89	3030	3020
1330	★	90		3011	
	+	91	91	3030	3020
2030	★	87		2938	
	+	87	87	2970	2954

III-7. OC.L Observed Fill Rate vs Buy Dollars.



POLICY		REQ FILL % OBS	REQ FILL % AVE	BUY-$ OBS	BUY-$ AVE
1030	*	88	88	1822	1826
	+	89		1830	
1130	*	87	87	1822	1826
	+	87		1830	
1230	*	87	87	1822	1826
	+	87		1830	
1330	*	87	88	1822	1826
	+	89		1830	
2030	*	83	82	1709	1709
	+	82		1710	

III-8. SM.L Obserrved Fill Rate vs Buy Dollars.

less money to achieve a higher fill rate. As shown in Figure III-5, policy code 10 dominates the results for policy codes 11, 12, and 20, and matches the results for policy code 13. Similar findings apply to Figures III-6 thru III-8. Note that Policy Code 20 was dominated by Policy Code 10 in all item samples. As a result, Policy code 20 was dropped from further consideration in our search for improved inventory management policies.

Tables III-2 and III-3 summarize the average requisition delay and fill rate results for policy codes 10, 11, 12, and 13. All of these runs used the current D062 safety level formulas and an implied shortage cost of $500. Thus the inventory management formulas would have computed exactly the same order levels and the order quantities for a given item under all four of these policies. Consequently, any differencies in observed results among these runs are due to the impact of variability in either the lead time or requisition generation procedures.

A very interesting and surprising statistic emerges from these tables. Notice that the simulation runs which involve a random lead time have better requisition delay and fill rate statistics then the corresponding runs in which the lead time was treated as a constant ! That is, when the lead times were random we observed better results. How can that be? What could have caused this result?

Table III-2

AVERAGE REQUISITION WEEKS DELAY

POLICY		OC.H				SM.H				OC.L				SM.L			
		OBS	AVE	%	Rank	OBS	AVE	%	Rank	OBS	AVE	%	Rank	OBS	AVE	%	Rank
1030	*	1.09				1.20				1.65				2.00			
	+	1.10	1.10	1.00	2	1.12	1.16	1.00	3.5	1.47	1.56	1.00	2	1.82	1.91	1.00	2
1130	*	1.13				1.08				1.89				2.19			
	+	1.16	1.15	1.04	3	1.10	1.09	.94	2	1.93	1.91	1.22	3	2.16	2.18	1.14	3
1230	*	1.28				1.17				1.96				2.27			
	+	1.28	1.28	1.16	4	.14	1.16	1.00	3.5	1.97	1.97	1.26	4	2.21	2.24	1.17	4
1330	*	.99				1.12				1.59				1.94			
	+	1.00	1.00	.91	1	1.04	1.08	.93	1	1.47	1.53	.98	1	1.76	1.85	.97	1
2030	*	7.42				1.77				2.20				3.18			
	+	1.70	1.36	1.42	5	1.97	1.87	1.61	5	2.34	2.27	1.45	5	3.41	3.30	1.72	5

Policy	Pri 2 %	Random Leadtime
1030	.5	yes
1130	0	no
1230	.5	no
1330	0	yes
2030	.5	yes

* = Fixed Requisition Stream
+ = Variable Requisition Stream

Table III-3

REQUISITION FILL PERCENT

POLICY	OC.H				SM.H				OC.L				SM.L			
	OBS	AVE	%	Rank	OBS	AVE	%	Rank	OBS	AVE	%	Rank	OBS	AVE	%	Rank
1030 *	92				91				90				88			
+	92	92	1.00	1.5	91	91	1.00	2.5	91	91	1.00	1.5	89	88	1.00	1.5
1130 *	91				91				89				87			
+	91	91	.99	3.5	91	91	1.00	2.5	89	89	.98	3.5	87	87	.99	3.5
1230 *	91				91				89				87			
+	91	91	.99	3.5	91	91	1.00	2.5	89	89	.98	3.5	87	87	.99	3.5
1330 *	92				91				90				87			
+	92	92	1.00	1.5	91	91	1.00	2.5	91	91	1.00	1.5	87	88	1.00	1.5
2030 *	90				87					87				82		
+	90	90	.98	5	87	87	.96	5	87	87	.96	5	82	82	.93	5

Policy	Pri 2 %	Random Leadtime
1030	.5	yes
1130	0	no
1230	.5	no
1330	0	yes
2030	.5	yes

* = Fixed Requisition Stream
+ = Variable Requisition Stream

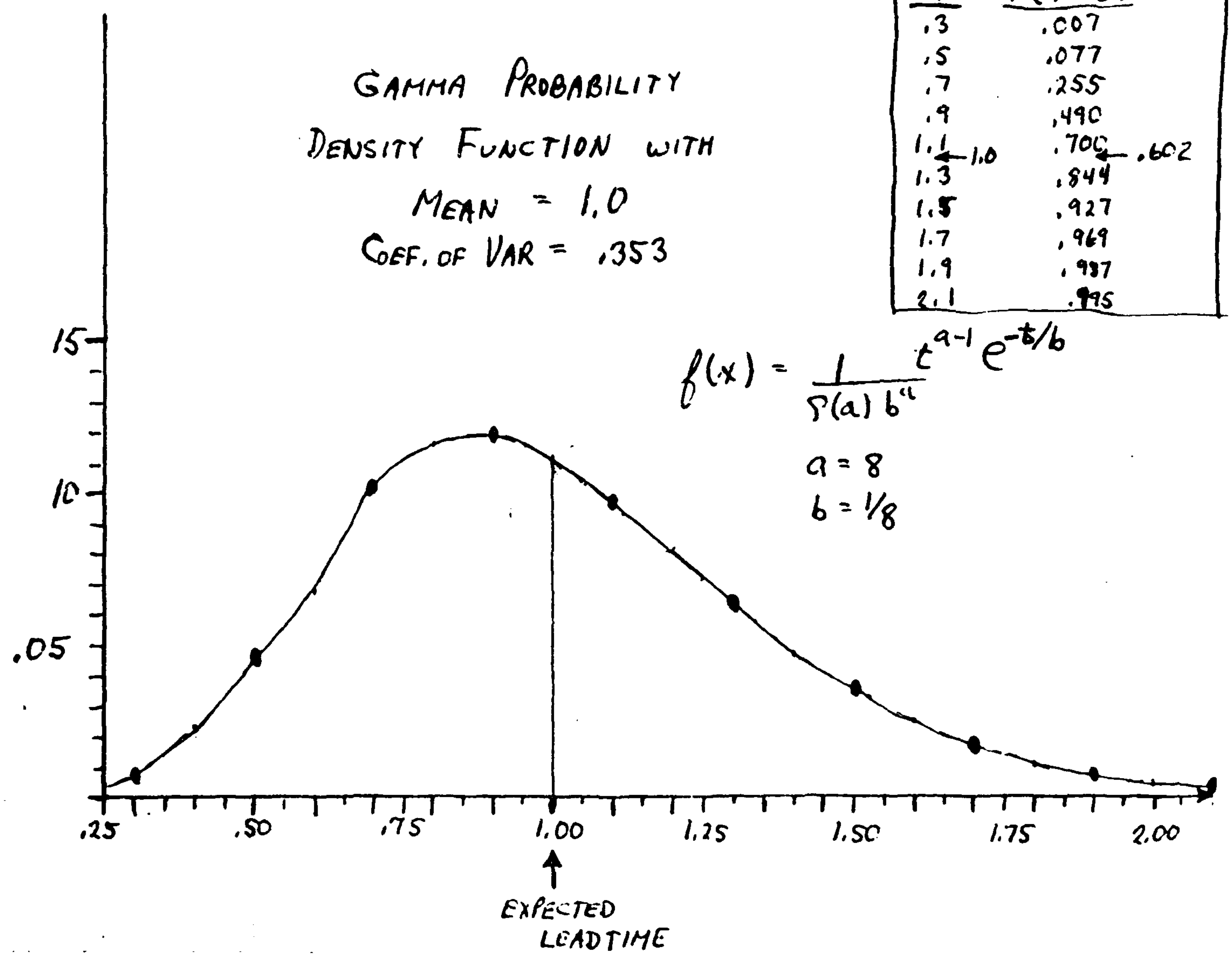
We believe that the explanation for the result lies in the method used to simulate lead times within the simulation. As noted above, all lead times were treated as gamma distributed random variables with a coefficient of variation of .353. The probability density function for this distribution is shown in Figure III-9. To represent this distribution within the simulation model, we recorded percentage points from the cumulative distribution function. The selected points are marked by the dots in Figure III-9. In the simulation model, we used linear interpolation to determine the specific lead time values which were between the tabulated points. Although this linear approximation appears to provide an excellent fit to the gamma distribution, it turns out that the average lead time generated by the linear approximation is approximately 95% of the specified mean value. That is, simulated lead-times drawn from this linear approximation to the gamma distribution average 5% less than the desired expected lead time for the gamma. Hence, in all simulation runs which involve random lead times, the simulated lead times averaged approximately 5% less than in those simulation runs in which the lead time was treated as a constant. The shorter mean lead time should have resulted in better supply effectiveness, but the variability in lead time should produce an opposite tendancy. In our runs, significantly improved effectiveness was observed. This may demonstrate that supply effectiveness is extremely sensitive to errors in mean lead time estimates. However, additional research is needed to test this conjecture.

GAMMA PROBABILITY
DENSITY FUNCTION WITH
MEAN = 1.0
COEF. OF VAR = .353

t	$P(T<t)$
.3	.007
.5	.077
.7	.255
.9	.490
1.1 ← 1.0	.700 ← .602
1.3	.844
1.5	.927
1.7	.969
1.9	.987
2.1	.995

$$f(x) = \frac{1}{\Gamma(a)\, b^{a}} t^{a-1} e^{-t/b}$$

$a = 8$
$b = 1/8$



III-9. Gamma Density Function with Mean = 1.0 and Coefficient of Variantion = .353.

All of the simulation runs reported in the next section used the same linear approximation lead time generation process as described above. Thus, each of the runs would have used simulated lead times that averaged about 95% of the estimated lead time values used in the inventory control level calculation formulas. Fortunately, since all of the formulas were subject to the same lead time generation process, estimates of the relative effectiveness of the alternate inventory policies should not be effected by the simulated bias in the estimated lead time values. In the next section, we discuss the relative performance of the alternate formulas.

Section IV

Comparison of Alternate Inventory Management Policies

Introduction

The objective of this study is to evaluate the relative cost effectiveness of several proposed methods for managing EOQ inventories when lead times are subject to significant variability. In this section, we report the results of simulation experiments to evaluate the performance of the alternate policies discussed in detail in Section I. For convenience, Table IV-1 summarizes the major inventory management policies considered. As noted in Section III, our initial pilot tests indicated that Policy Code 20 was inferior to Policy Code 10 techniques, and consequently Policy Code 20 was deleted from consideration in this Section.

Measures of Effectiveness

A critical issue in every management situation is to establish appropriate criteria for selecting among proposed alternatives. Ideally, we would like to select an inventory management policy which provides the most effective means of accomplishing Air Force programs. We would particularly like to be able to spend procurement dollars in a manner that would provide the maximum

Table IV-1

Inventory Management Policy Codes

Code	Inventory Management Policy
10	Current D062 Formulas
20	Current D062 Formulas, with outliers excluded from demand and variance estimates
60	Current D062 Formulas, with adjustments to standard deviation of lead time demand to account for lead time variability
70	Scaled Negative Binomial reorder point calculations, with no bounds on safety level
80	Constant Leadtime Exponential Forecast Error model, with no upper bounds on safety level
90	Exponential-Gamma Forecast Error Model, with no bounds on safety level

system effectiveness for a given level of expenditure. Unfortunately, the linkage between aircraft availability and depot level inventory policies is very complex, and analytical methods for quantifing these relationships are not available. Consequently, several other depot-level performance measures have been utilized in past studies as a basis of comparision among alternate inventory management policies. Measures of effectiveness which are particularly relevent to this effort include:

Requisition fill rate.

Unit fill rate.

Average requisition delay time.

Average unit delay time.

Long supply dollars.

Procurement expenditures.

There is, of course, a close relationship among all of these measures. In particular, the more money that is expended for safety stocks, the higher the level of supply effectiveness and long supply that may be expected. Figure IV-1 illustrates a hypothetical fill rate-Buy Dollar curve. As shown in the figure, as Buy dollars increase, the fill rate associated with the supply system would also be expected to increase.

Unfortunately, it is computationally prohibitive to evaluate each proposed policy for each possible funding level. Consequently, to keep computational needs within reasonable limits, we evaluated

each proposed inventory management policy for each sample at six different support levels. This permits us to develop a six-point approximation to the underlying cost effectiveness curve for each formula. By connecting the resulting fill rate and Buy dollar points, we obtain an approximation to the "true" underlying cost effectiveness relationship. If these points are close together on the effectiveness curve, a linear approximation obtained in this way should provide a good approximation to the true underlying curve. On the other hand, if the resulting points are widely spaced, such a linear approximation may provide a very poor fit to the underlying theoretical curve. For example, if the points A and C in Figure IV-1 are joined, the resulting linear approximation is a poor estimate for the point B shown in the figure.

Figure IV-2 illustrates a hypothetical curve relating expected average delays versus procurement expenditures. In this case, the higher levels of procurement expenditures should result in reduced requisition backorders and reduced delays in filling an average requisition. Low funding levels should result in relatively high average delays, while high funding levels should result in very short delays. In simulating a specific policy, we will of course obtain only single points, such as those illustrated by "*" Figure IV-2. In this case, connecting the observed average delay vs Buy dollar points will result in a upper bound to the underlying curve.

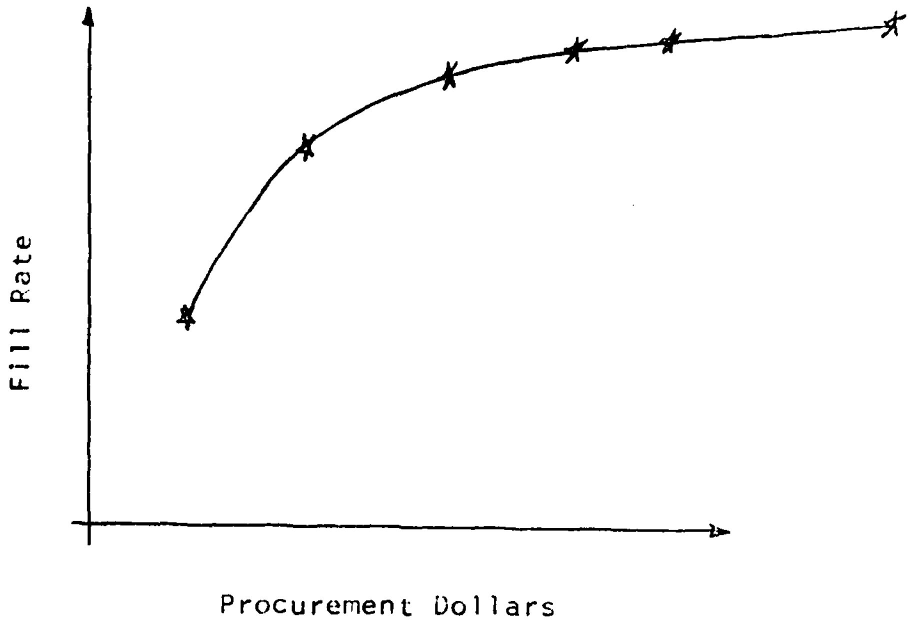


Figure IV-1. A Hypothetical Fill Rate Vs Buy Dollar Curve.

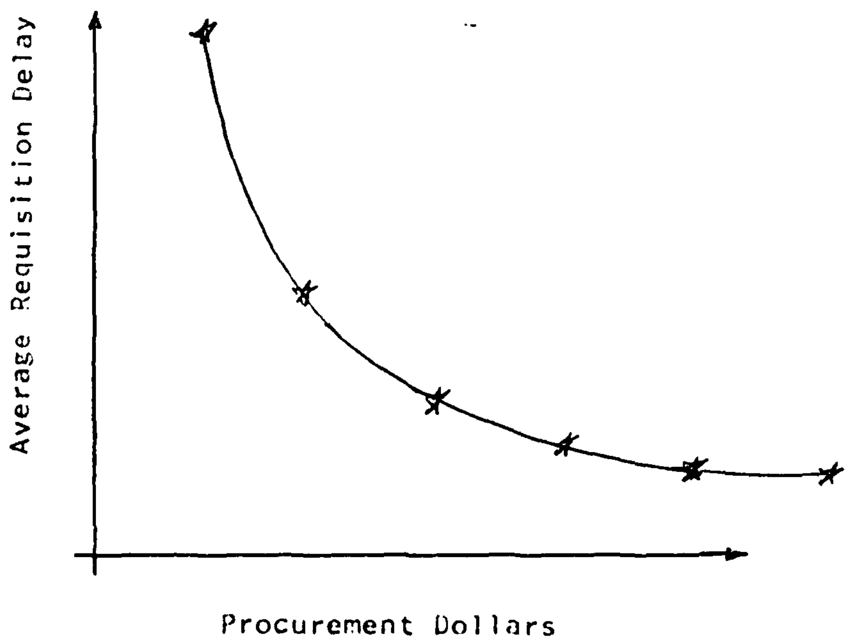
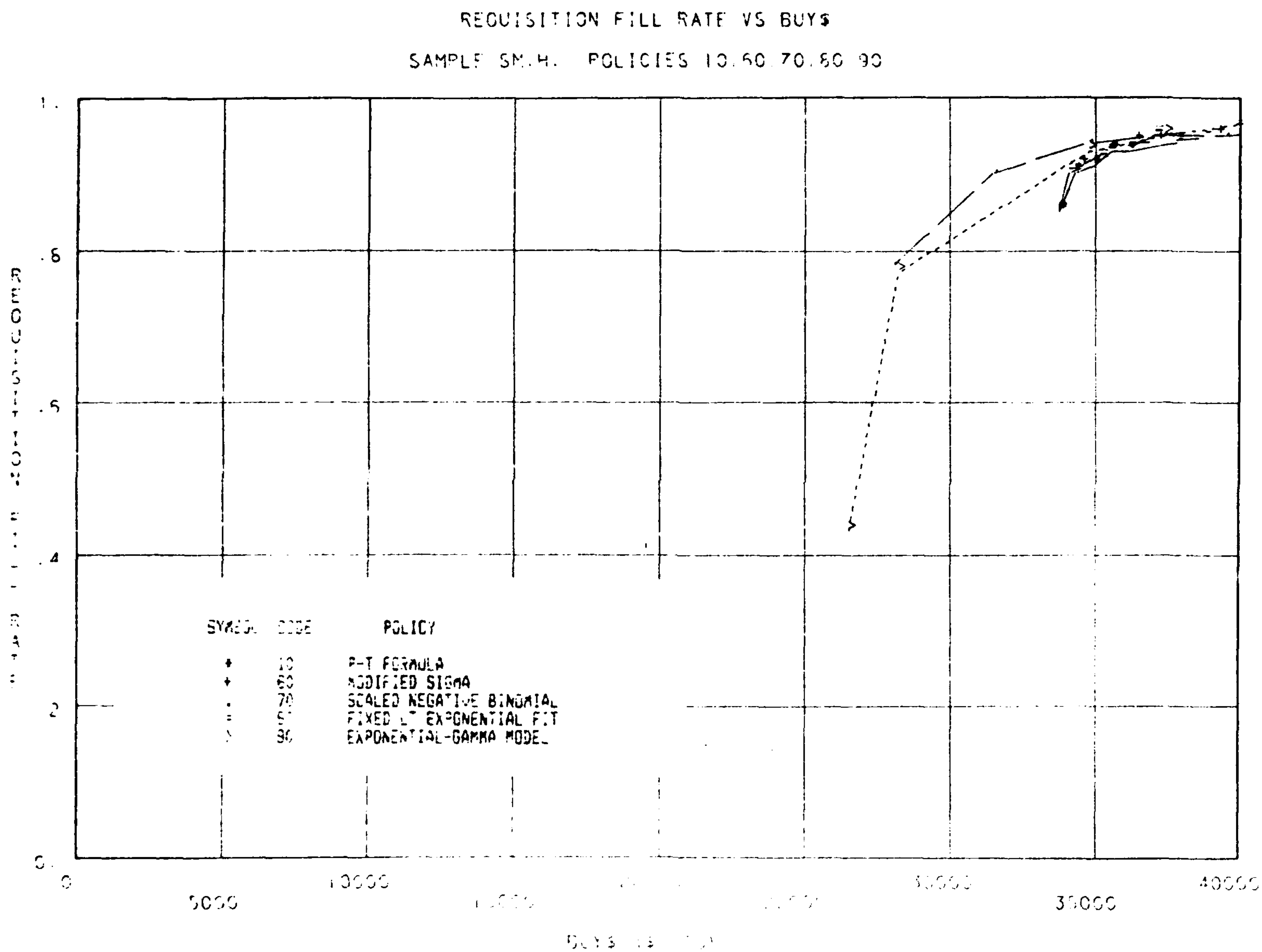


Figure IV-2. A Hypothetical Delay vs Buy Dollar Curve.

Simulation Results for Sample SM.H

As discussed in Section I, we simulated each of the proposed inventory management policies using each of four separate item samples. In the following paragraphs, we present the detailed support effectiveness curves obtained for the sample SM.H, i.e. for the high activity sample selected from Sacremento Air Logistics Center history records. Similar curves for samples OC.H, SM.L, and OC.L are presented in Appendices A, B, and C, respectively.

Figure IV-3 presents requisition fill rate vs Buy dollar curves observed from our 30 quarter simulation of sample SM.H. Recall that policies 70 and 90 have no lower bounds on safety levels. Consequently, these policies are able to spend less money than the other inventory management policies. On the other hand, Policy Codes 10, 60, and 80 have a lower bound of zero on the safety stock; i.e. the reorder lever for these policies is bounded to be at least equal to the expected demands in a lead time. For very low values of the implied shortage cost, all of these policies will compute negative safety levels as being optimal. However, because of the lower bounds, the computed safety level for Policies 10, 60, and 80 will be reset to zero in this event. The result is that Policies 10, 60, and 80 all have the same reorder levels for very low values of the implied shortage cost. As shown in Figure IV-3, all of the lower bounded policies spend at least 34 million dollars over the 30 quarter simulation. Note that these policies result in lower requisition fill rates for a $34 million expenditure than the fill rates produced by Policy Code 70 or Policy Code 90 at this spending level. At higher funding levels, it is difficult to distinguish among the five curves at this level of plot resolution. Consequently, in Figure IV-4, we provide a "magnified" look of the requisition fill rate vs Buy $ curve. As shown in the figure, all of the proposed alternative policies dominate Policy Code 10, the current D062 policy. However, the alternative curves "cross-over" for procurement dollars between 34 and 38 million dollars and it is difficult to select a single policy as the optimal one in this region.



IV-3. SM.H Requisition Fill Rate vs Buy Dollars.

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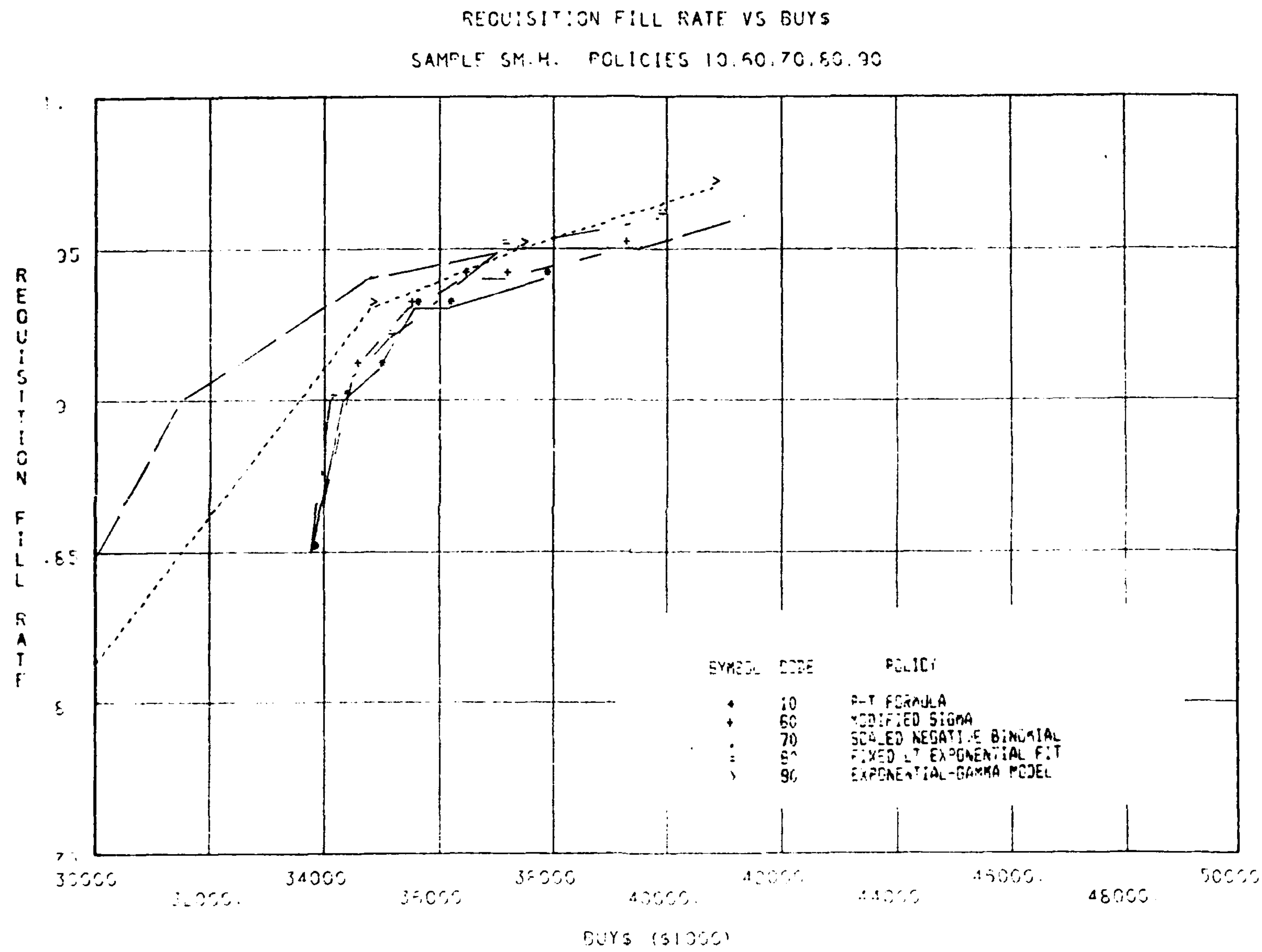

IV-4. SM.H Requisition Fill Rate vs Buy Dollars--Close-Up.

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In Table IV-2, we have summarized our rankings of the alternate inventory management policies under each of the proposed measures of effectiveness. As we have just observed, all four of the Policy Codes 60, 70, 80, and 90 appear superior to Policy Code 10 results with respect to the requisition fill rate measure. Consequently, in Table IV-2, we have assigned each of these four policies of equal rank, and all of them are ranked as being superior to Policy Code 10.

Let us now consider our results for unit fill rates. Figures IV-5 and IV-6 plot unit fill rate vs buy dollar curves observed in simulating sample SM.H. Note that it is difficult to distinguish among the curves when we use the scaling presented in Figure IV-5. Consequently, let us consider the "close-up" plot presented in Figure IV-6. As shown in the figure, Policy Code 10 is dominated by the other four proposed alternatives. In this figure, Policy Code 90 dominates the results for all other policies. That is, Policy Code 90 produces a higher fill rate at a given level of buy dollars than all of the other policies. Conversely, a given fill rate may be achieved at a lower funding level using Policy Code 90 than is possible using any of the other proposed methods. Note that Policy Code 70 does very well at extremely low funding levels. However, Policy 70 is dominated by Policy Code 80 for funding levels in the $36 million or more range. Further, observe that the Policy Code 60 produces results superior to Policy Code 10 under all funding levels, but that Policy Code 60 is dominated by the other three proposed inventory management

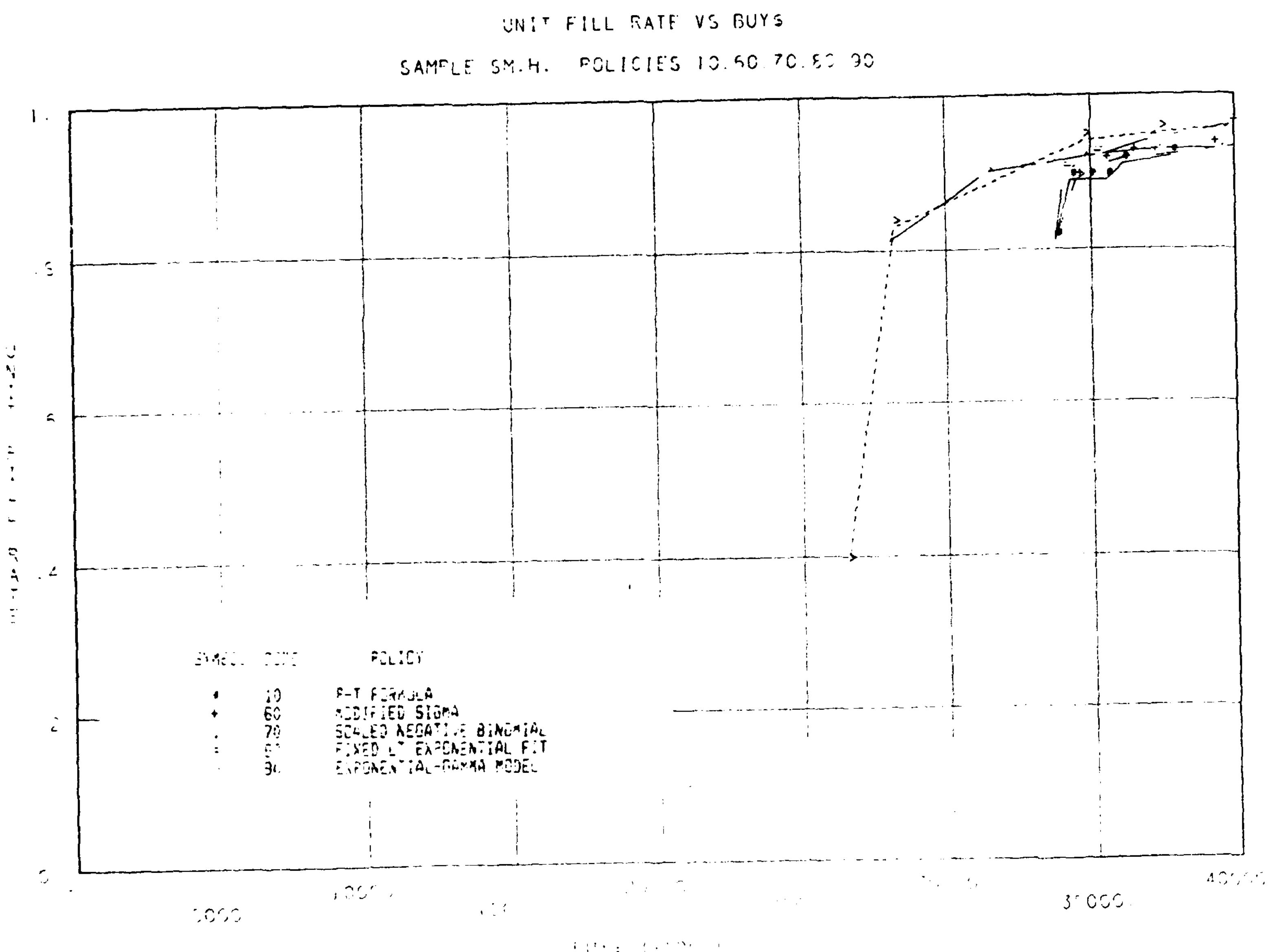
Table IV-2

Policy Rankings for
Several Support-Effectiveness Measures

SAMPLE

Measure	SM.H	OC.H	SM.L	OC.L	Combined Ranking
Requisition Fill Rate	90 , 10 80 70 60	90 80 70 60 10	90,80, 60 ,10 70	90, 80 ,60,10 70	90,80,70,60,10
Unit Fill Rate	90,80,70,60,10	90,80, 60 ,10 70	90,80, 60 ,10 70	90,80, 60 ,10 70	90,80,70,60,10
Ave-Unit-Delay	90,80,70,60,10	90, 80 ,10 70 60	90 , 70, 10 80 60	90 , 80 ,10 70 60	90,80,70,60,10
Ave-Requisition -Delay	90 80 70 60 10	60 , 90 70 80 10	90 , 70,10 80 60	90 , 60 80 10 70	70, 90 ,60,10 80 90,80, and 70 all close
Long Supply At End	70, 60 ,90,80 10	90 ,70,80 60 10	90 , 80 60 70 10	70,60,90,10,80	60, 90 ,80 70 10

Note: Left-to-right = decreasing rank
down = same rank



IV-5. SM.H Unit Fill Rate vs Buy Dollars.

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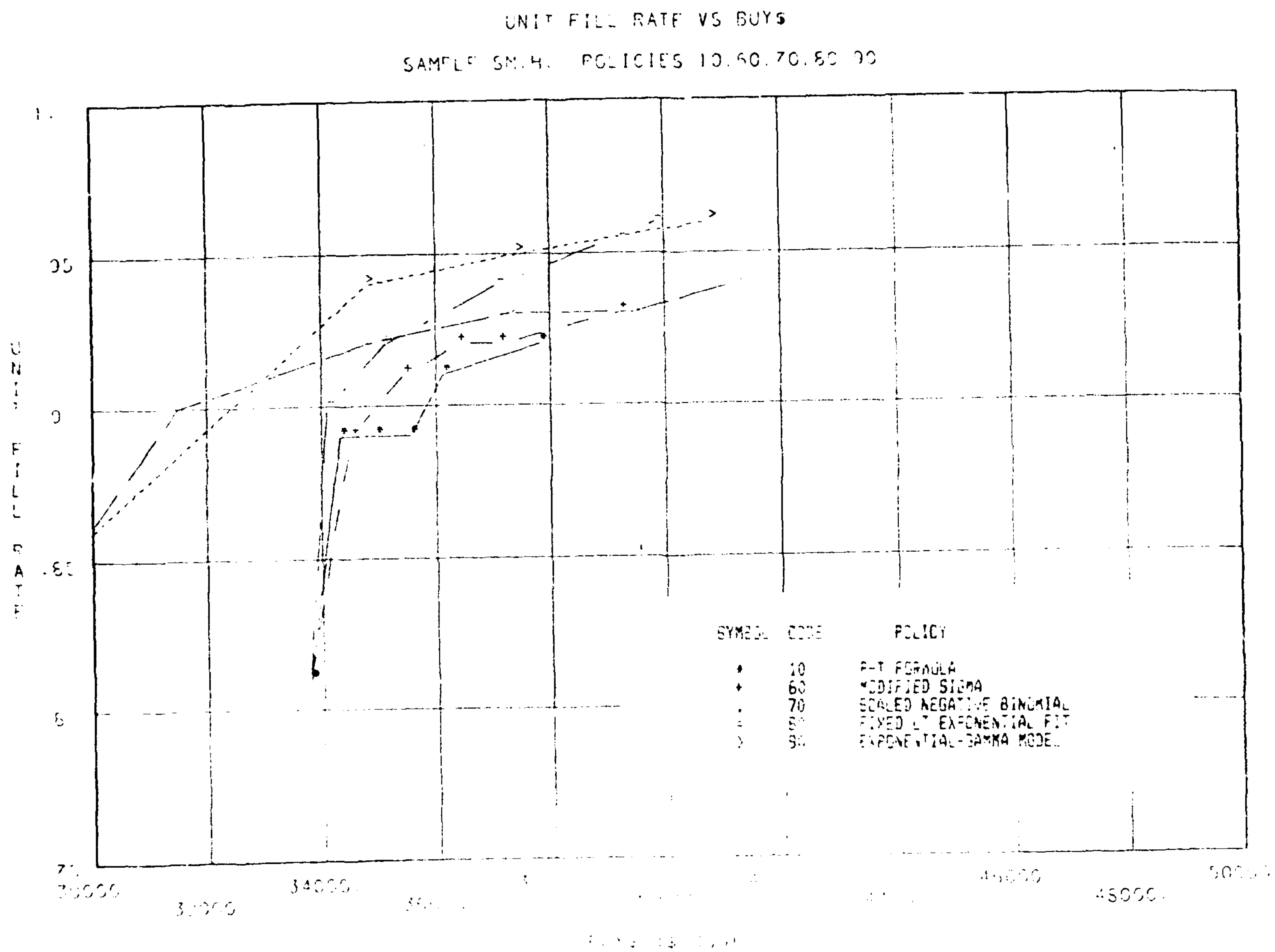

IV-6. SM.H Unit Fill Rate vs Buy Dollars--Close-Up.

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AD-A124 618 AN EVALUATION OF ALTERNATE D062 INVENTORY MANAGEMENT POLICIES WHEN LEADTIMES ARE RANDOM(U) DECISION SYSTEMS BEAVERCREEK OH W S DEMMY SEP 81 WP-81-07

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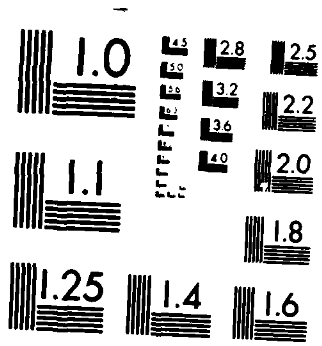
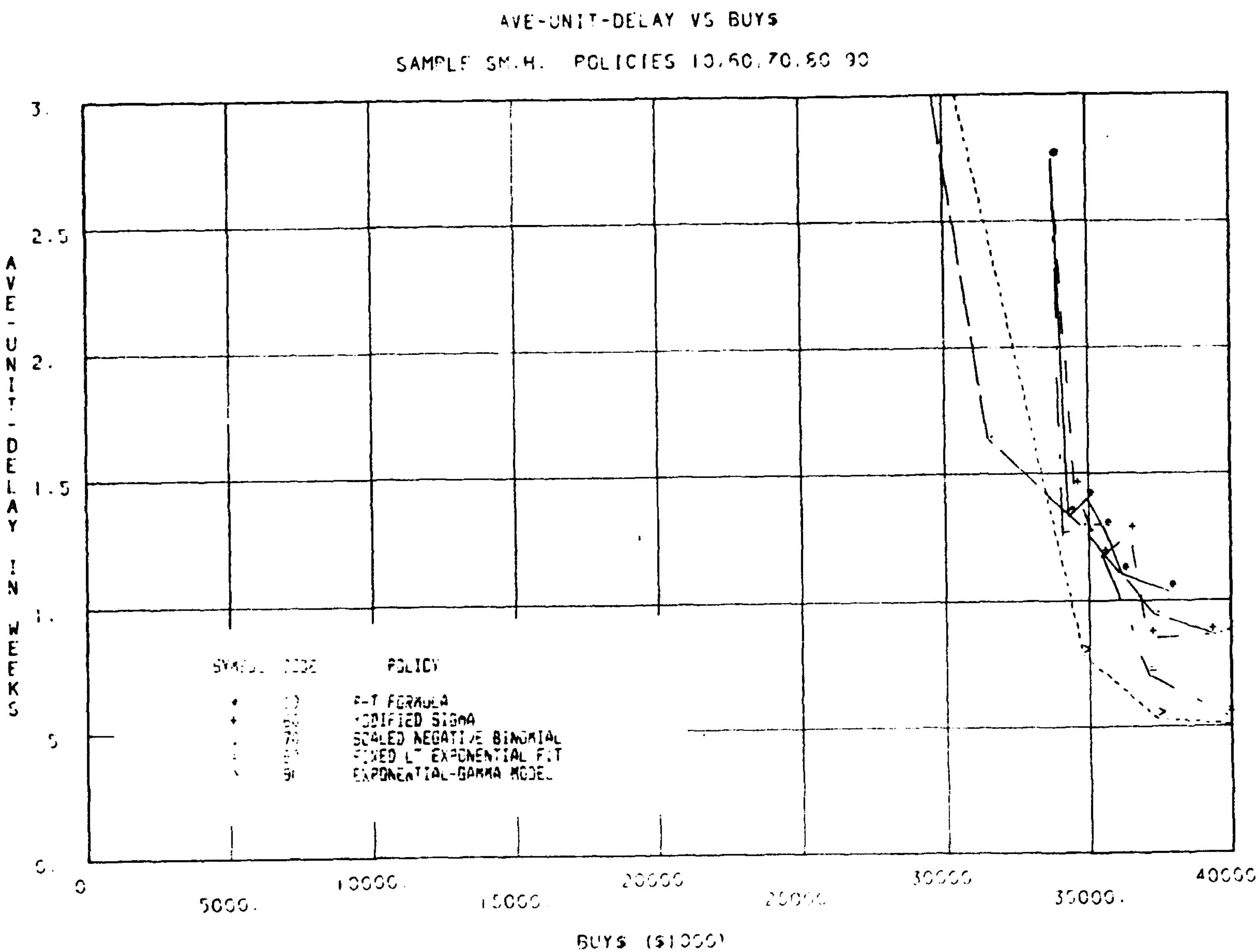

1.0
1.1
1.25
1.4
1.6
1.8
2.0
2.2
2.5
2.8
3.2
3.6
4.0

methods. In Table IV-2, we have summarized these results by ranking the proposed inventory management policies as 90, 80, 70, 60, and 10, in descending order of preference with respect to unit fill rate criterion.

Figures IV-7 and IV-8 plot the observed average unit delay vs buy dollar curves for sample SM.H. As shown in Figure IV-8, Policy Code 90 clearly dominates the other methods for procurement expenditures of 34 million dollars or more, while Policy Code 80 appears to be the second best policy. The other three cost effectiveness curves cross. However, we believe that three remaining curves should be ranked in the order of 70, 60, 10, in descending order of preference. In particular, note that Policy Code 10 is dominated by Policy Codes 90, 80, and 70 at all funding levels.

Figures IV-9 and IV-10 plot average requisition delay vs buy dollar results for sample SM.H. For extremely low funding levels, Policy Codes 90 and 70 produce average requisition delays as good as those produced by the lower bounded policies, but Policies 90 and 70 required from 2 to 4 million dollars less to achieve these results. On the other hand, for procurement expenditures of $35 million or more, all of the curves cross, and it is very difficult to distinguish a dominant policy. As a result, we have ranked all of these policies as being equal with respect to the average requisition delay criterion.

Figures IV-11 and IV-12 plot long supply statistics verses



IV-7. SM.H Average Unit Delay vs Buy Dollars.

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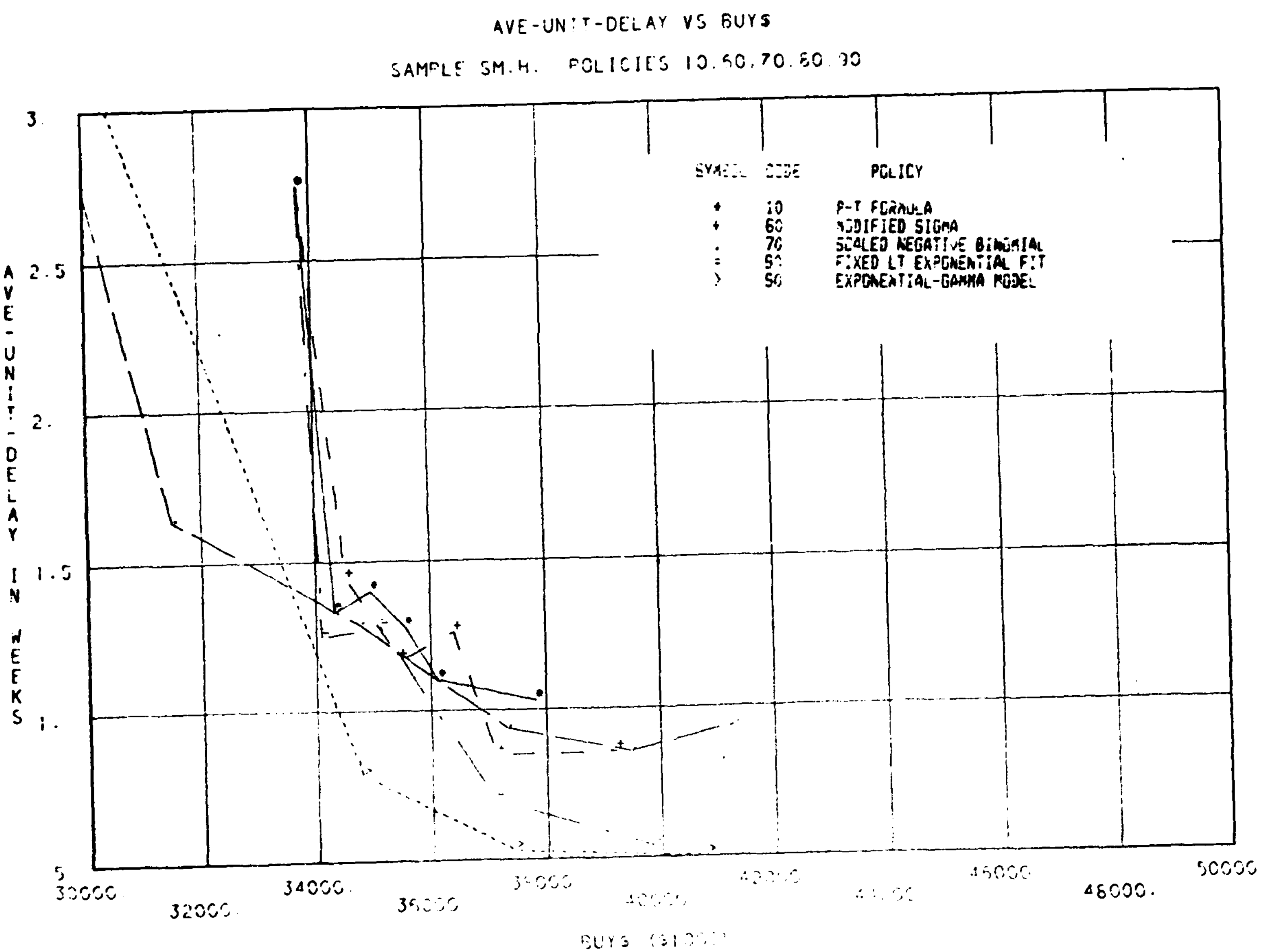

IV-8. SM.H Average Unit Delay vs Buy Dollars--Close-Up.

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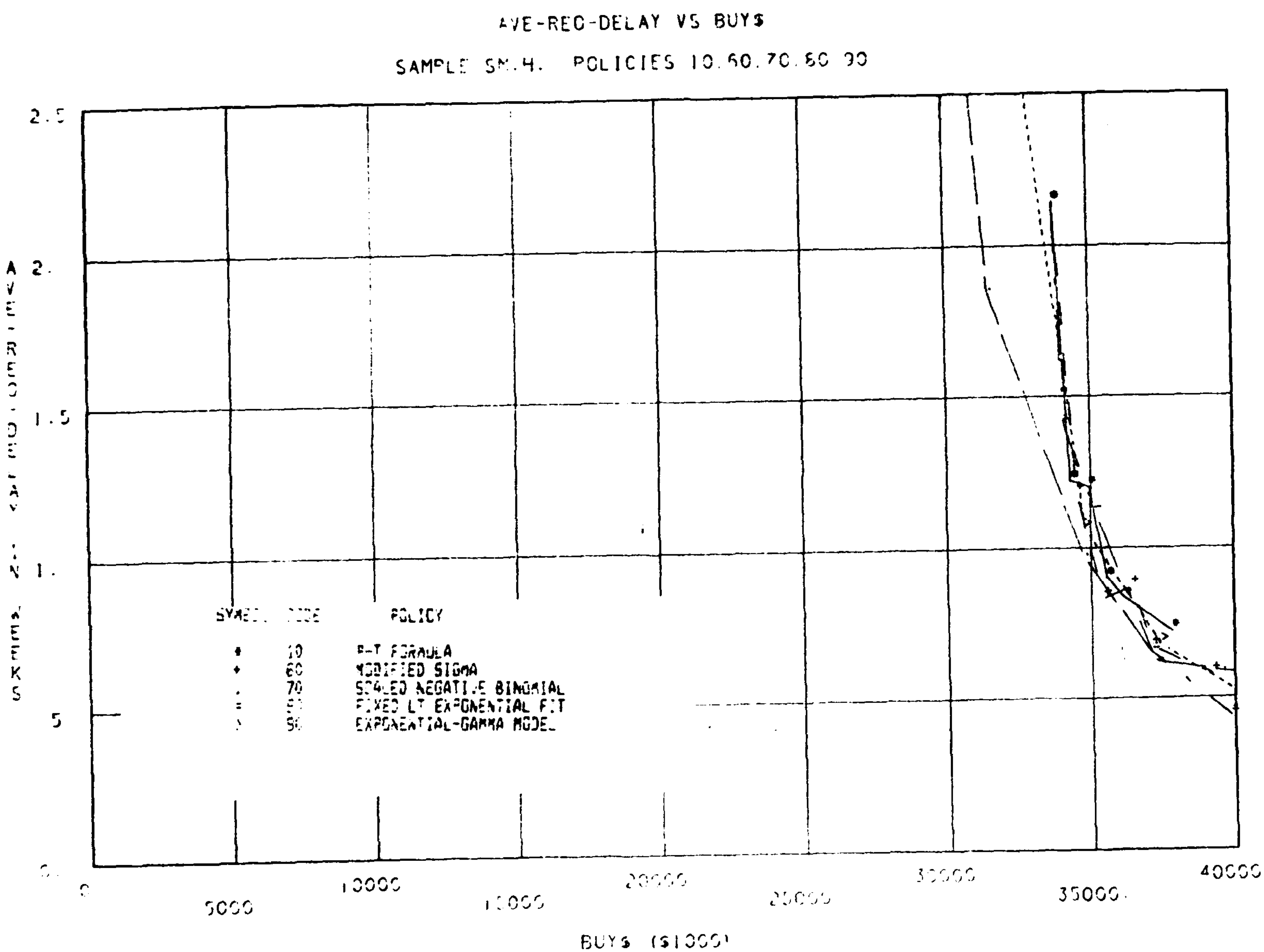
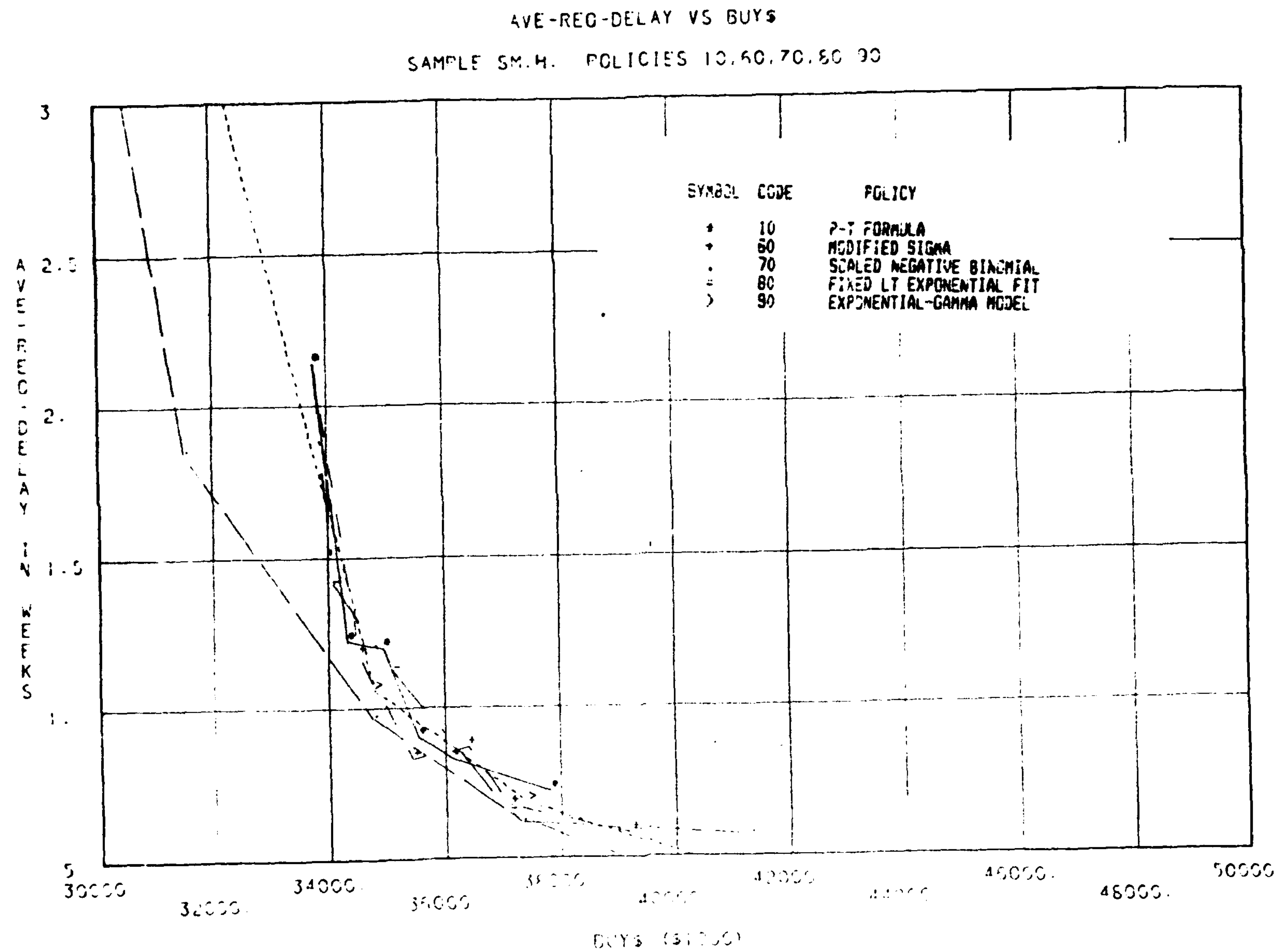


IV-9. SM.H Average Requisition Delay vs Buy Dollars.



IV-10. SM.H Average Requisition Delay vs Buy Dollars--Close-Up.

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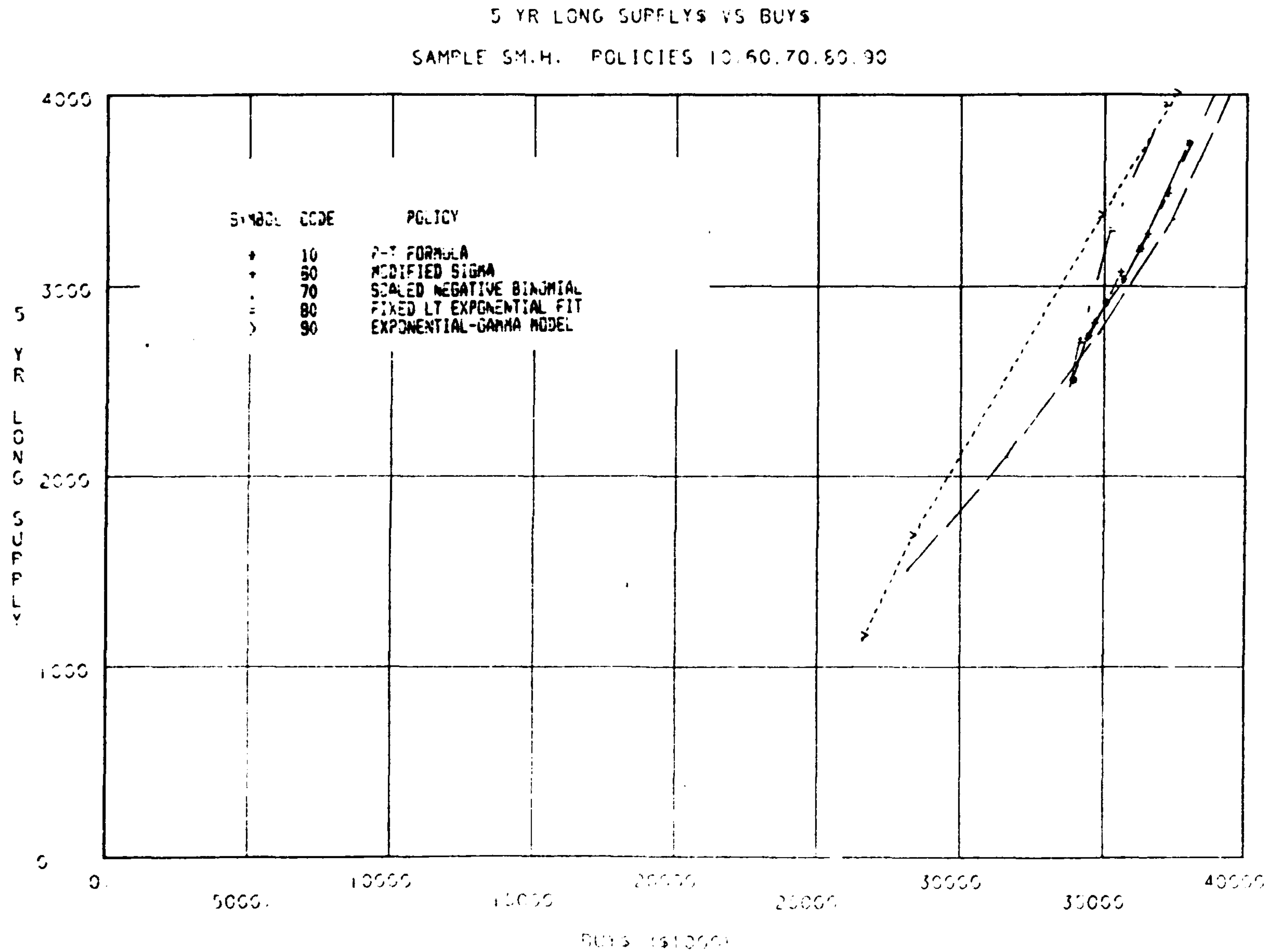
buy dollars. We use the term "five year long supply" to represent the dollar value of stock which is more than five years of supply in excess of the Air Force Acquisition Objective at the end of the simulation. As shown in these figures, for a given procurement dollar expenditure, Policy Code 70 results in the low levels of long supply at the end of the 30 quarter interval. Policy Codes 10 and 60 provide almost identical results. Finally, Policy Codes 80 and 90 provide the highest levels of five-year long supply associated with a given procurement expenditure level.

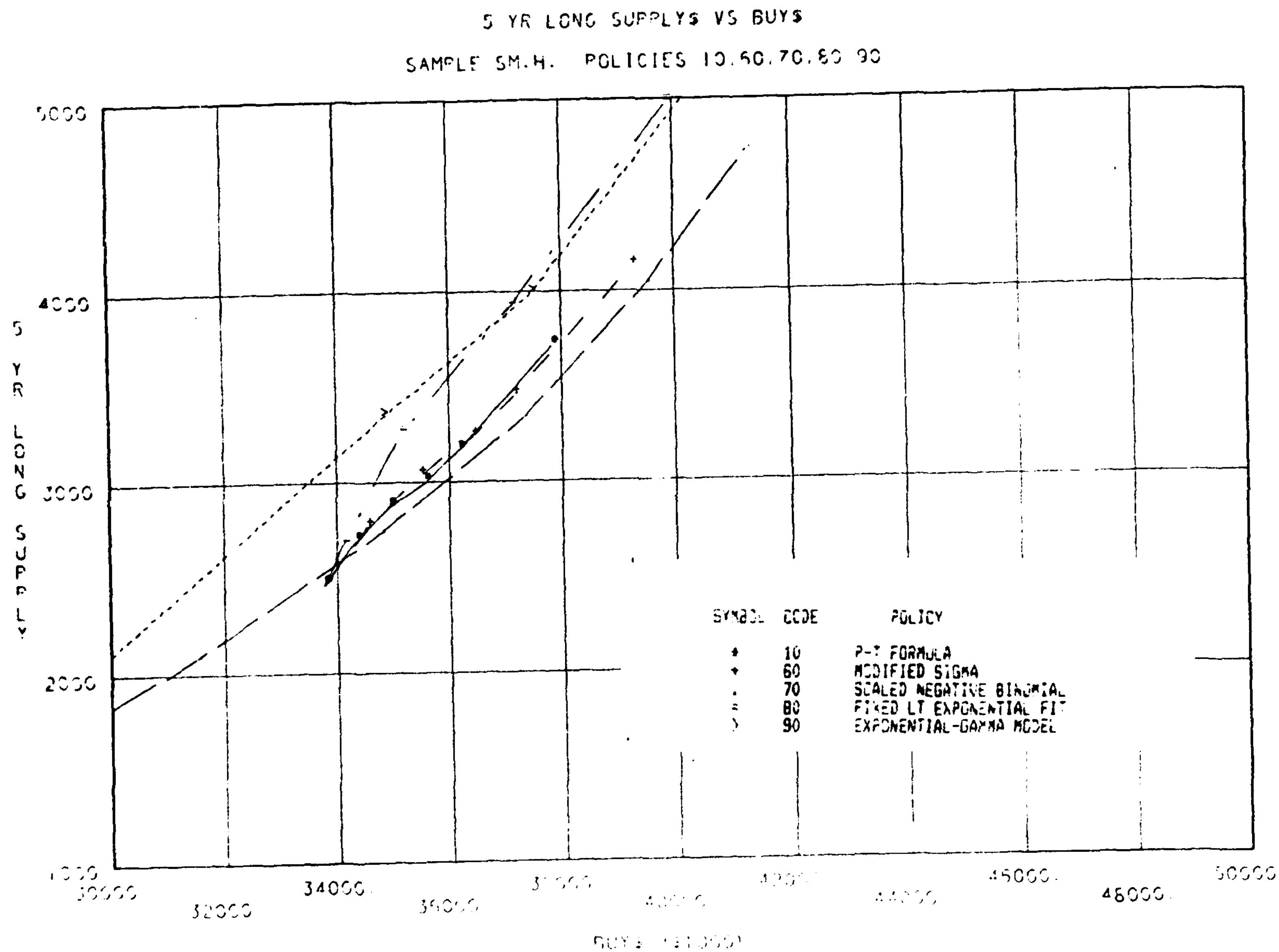
Simulation Results for Samples OC.H, SM.L, and OC.L

The detailed fill rate and average delay curves obtained from simulations of samples OC.H, SM.L, and OC.L are presented in Appendices A, B, and C, respectively. Our evaluation of the relative dominance of each of these policies with respect to each measure of effectiveness is presented in Table IV-2. On the right hand side of Table IV-2 we present a combined ranking of the alternate policies. This combined ranking is based on the arithmetic average of the ranks associated with each policy for each of the item samples.

Let us now consider Table IV-2 in more detail. As shown in the table, all five policies were ranked as equal with respect to requisition fill rate for the high activity samples SM.H and



IV-11. SM.H Long Supply vs Buy Dollars.



IV-12. SM.H Long Supply vs Buy Dollars--Close-Up.

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OC.H. On the other hand, for the low activity samples SM.L and OC.L, Policy 90 clearly produced superior requisition fill rate statistics. Similarly, Policy Code 80 was ranked either second or tied for second in both of these low activity samples while Policy Code 10 was dominated by all four alternatives in both of these low activity runs. The arithmetic average of the ranks given above results in a combined ranking of 90, 80, 70, 60, and 10, in decreasing order of preference for these alternative policies.

Let us now consider the rankings for the unit fill rate criterion. As shown in Table IV-2, Policy Codes 90 and 80 were the first and second best policies in all four of these item samples, while Policy Code 10 was ranked last in each case. The combined ranks resulted in the relative order of preference for the four policies of 90, 80, 70, 60, and 10.

In the average unit delay versus buy dollars curves, Policy Code 90 again dominates the other four alternatives, while Policy Code 10 produces the worst results. In this case, several of the other curves cross for specific samples, and consequently these curves were ranked as equal in those samples. However, when average ranks are computed, we would again obtain the 90, 80, 70, 60, and 10 sequence.

We obtained very mixed results for the average requisition delay statistic. As shown in Table IV-2, we could not distinguish a dominant policy for this measure for sample SM.H. For

sample OC.H, Policy Codes 60 and 70 appear to dominate, while Policy Codes 90, 80 and 10 were ranked as about equal but inferior to Policy Codes 60 and 70. For the low activity samples, Policy Codes 90, 80, and 70 appear to produce the best results, while Policy Code 10 was ranked last. When average ranks are computed, Policy Code 70 has the highest average rank and Policy Code 10 has the lowest rank. However, the average ranks of Policy Codes 70, 80, and 90 are all very close to one another and they are all significantly better than the average rank for Policy Code 10.

Finally, let us consider the plots of long supply vs procurement dollars. In this case, we again obtained mixed results. However, Policy Codes 70 and 60 are rated better than the other alternatives, while Policy Code 80 tends to be ranked last. When average ranks are computed for the four samples, Policy Code 60 has the best average rank, while Policy Code 80 has the worst average rank. The other three policies have the same average rank in this case.

Summary of Cost Effectiveness Comparisons

Which policy is best depends upon what criteria is used as a basis of judgement. We have observed that Policy Codes 90 and 80 produce consistently higher results for requisition fill

rates, unit fill rates and average unit delays, while Policy Code 10 is consistently worse than all the other alternatives with respect to these three measures. For average requisition delays, we observed mixed results. Policy Codes 60, 70, 80 and 90 were each ranked first or were tied with first in at least one of the four item samples, and all four of these policies appear to produce very similar results. However, Policy Code 10 was always ranked last with respect to the average requisition delay criteria.

Finally, if one considers the long supply statistics, we come up with an ordering of policies completely different from those observed in the above paragraph. The results in all four item samples were mixed. However, Policy Code 80 was ranked last in all four item samples while several of the proposed alternatives were ranked first with respect with the long supply statistic.

SECTION V

Summary of Results

This paper presents the results of simulation experiments to evaluate the relative effectiveness of six alternative rules for managing Air Force EOQ inventories when procurement leadtimes are random variables. Detailed descriptions of these rules are presented in Section I. The Inventory System Simulator (INSSIM) was used to evaluate each of the proposed rules under several different funding levels. INSSIM provides a detailed description of the D062 Economic Order Quantity Buy Computation System and uses actual Air Force demand histories to drive the simulation process. For the study, four item samples of up to 500 items each were selected from the INSSIM Data Bank.

The samples SM.H and SM.L were selected from Sacramento Air Logistics Center records, while samples OC.H and OC.L were selected from Oklahoma City ALC records. The high activity samples SM.H and OC.H consisted of items which had net demands in CY71-72 which exceeded $5000 per year, while the samples SM.L and OC.L consist of items with net CY71-72 demands which were less than $5000 per year.

Thirty-eight quarters of history covering the CY71-79 interval were available for each of these items. The first eight quarters of data were used to initialize the forecasting and inventory management rules, while the remaining 30 quarters of data were used to simulate the behavior of each of these rules. Thus, the simulation results evaluate how each of these rules would have performed had they been employed during the CY73-79 interval.

Section II describes the aggregate behavior of each of the item samples, while Section III presents measurements of the variability that is induced into the simulation results by the use of Monte Carlo techniques. In this section, we found that Policy 20 was inferior to the current D062 rules (Policy Code 10), and consequently Policy 20 was dropped from further consideration. Finally, Section IV presents supply effectiveness curves which quantify the relative performance of each of the remaining inventory management rules.

Table IV-2 summarizes our rankings of the relative performance of each of the proposed rules for each item sample and also presents a combined ranking based upon the arithmetic average of the individual sample ranks. We found that Policy Codes 90, 80, and 70 consistently outperform Policy Codes 60 and 10 for the requisition fill rate, unit fill rate, average and unit delay, and average requisition delay measures. Policy codes 90 and 80 performed particularly well for the low activity samples and for the unit-based measures of effectiveness. On the other hand, it was difficult to distinguish a superior policy for the requisition-based measures for the high activity samples.

When the long supply versus buy dollar curves were considered, we obtained mixed results. Policy Codes 90, 70, 60, and 10 were each ranked first or tied for first in at least one item sample, but Policy Code 80 was ranked last in all cases. This is a very interesting result, since Policy code 80 performed very well with respect to each of the fill rate and average delay statistics reported above. Apparently, Policy Code 80 achieves its

improved supply-effectiveness versus buy dollar performance by taking higher risks that some of its safety stocks will later be classified as excess.

Implications for the Management of Real World Inventories

This report presents quantitative evaluations of alternate inventory management policies in a simulated D062 environment. Although the simulation provides a detailed description of the D062 system, there are several important differences between the D062 simulation model and the actual D062 environment. These differences must be considered in determining an appropriate policy for the management of the actual D062 system.

First, in our simulation model the mean and variance of procurement lead times were known with certainty, while in practice, these parameters must be estimated from available data. We have observed that several policies significantly outperform the current D062 rules when accurate leadtime data is available. Unfortunately, the required data is not currently available in the D062 system, and it appears that a significant data processing effort would be required to routinely collect and update the needed information. Thus, implementation of Policies 90, 70, or 60 must either (a) await the development of such a system or (b) use regression or similar estimates as an interim measure. On the other hand, Policies 10 (the current rate) and 80 do not require these parameters.

Second, in our simulation model we have perfect information concerning item requisition counts. In previous studies we have found that D062 requisition counts are extremely unreliable,

and we believe that any formula that uses D062 requisition count data is basing Air Force safety stocks on a random number generator. This problem appears particularly severe for the very large number of low activity items managed by the D062 system. Hence, we believe the data processing rule of garbage in--garbage out would describe the results of implementing any rule that uses requisition count data in the current D062 system. Thus, rules 70, 60, and 10 could be expected to perform much worse in the real world system than they have performed here until requisition count data accuracy can be improved.

Observe that Policy Code 80 is the only rule that avoids both of the severe data problems described above. Although Policy Code 90 provided results which were slightly superior to Policy 80 effectiveness curves, Policy 90 requires accurate estimates of lead time variability to deliver on its promise of superior performance. On the other hand, Policy 80 does not require this parameter. In addition, we believe that Policy 80 results could be further improved by reducing the lower limit on safety stocks.

Policy 80 has another clear advantage. Mathematically, Policy 80 is even simpler than the current Presutti-Tripp formulas, and only a few lines of computer code would need to be changed to implement this rule in D062, in INSSIM, in EOQSIM, or in any other data system that uses the current PT-formulas. An illustration of the FORTRAN code required to implement Policy 80 is presented in Decision Systems Working Paper 81-02, HEDGSIM Routines for Leadtime Variability Inventory Management Research, September 1981, in Subroutine LEVELN.

In summary, we believe that significant improvements in inventory management effectiveness may be achieved by replacing the current D062 safety level rules (Policy 10) by Policy 80 rules as soon as possible. On the other hand, if accurate leadtime and requisition count data were available, even better results should be obtained.

References

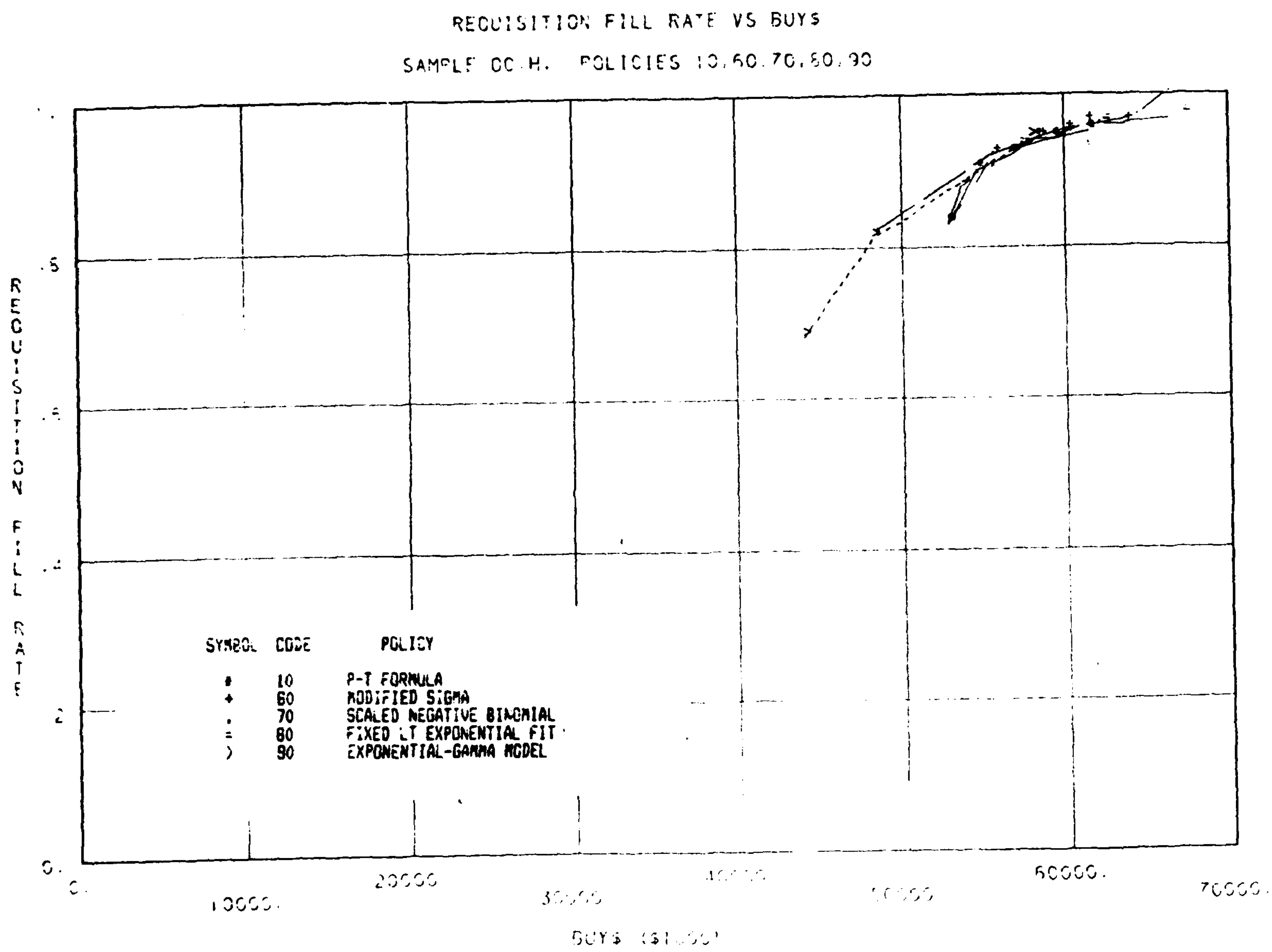
1. Demmy, W. Steven. HEDGSIM: The Long Supply Simulaton Model; Volume II, Program Listings and Narratives. Working Paper 80-10, Decision Systems, 2125 Crystal Marie Drive, Beavercreek OH 45431, December 1980, 97 pp.

2. Demmy, W. Steven. Modeling the Probability Distribution for Depot-Level Requisition Sizes. Working Paper 80-07, Decision Systems, 2125 Crystal Marie Drive, Beavercreek OH 45431, October 1980, 160 pp.

3. Hayya, Jack C. Lead Time Variability in Inventory Requirements Projections. Air Force contract 33615-79-C-5143, Item 0004, Phase 3, Technical Report and Summary, 1962, Norwood Lane, State College PA 16801, June 30 1980, 71 pp.

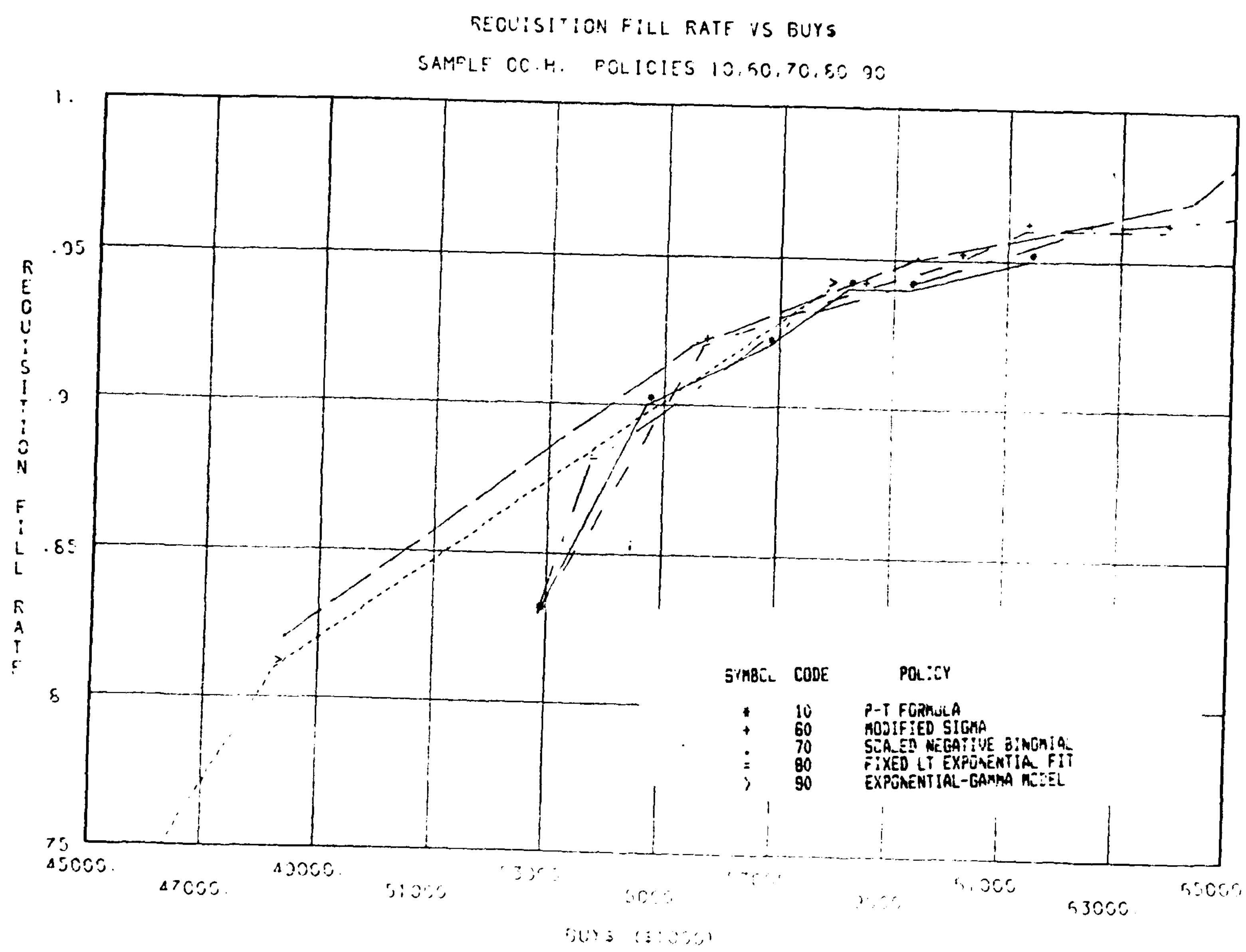
Appendix A

Cost Effectiveness Curves for Sample OC.H



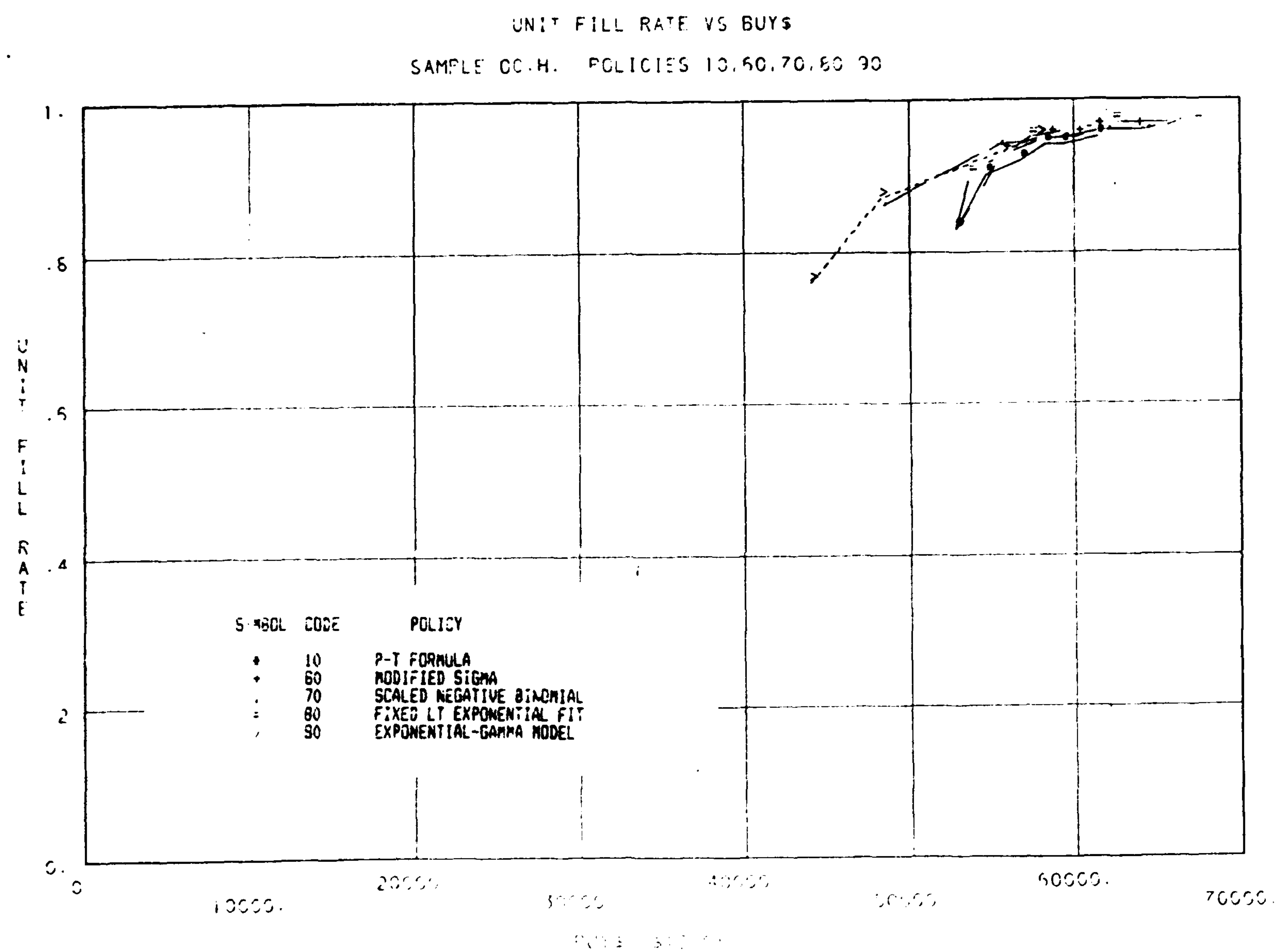
A-1. OC.H Requisition Fill Rate vs Buy Dollars.

#1
C863T
10-6-81



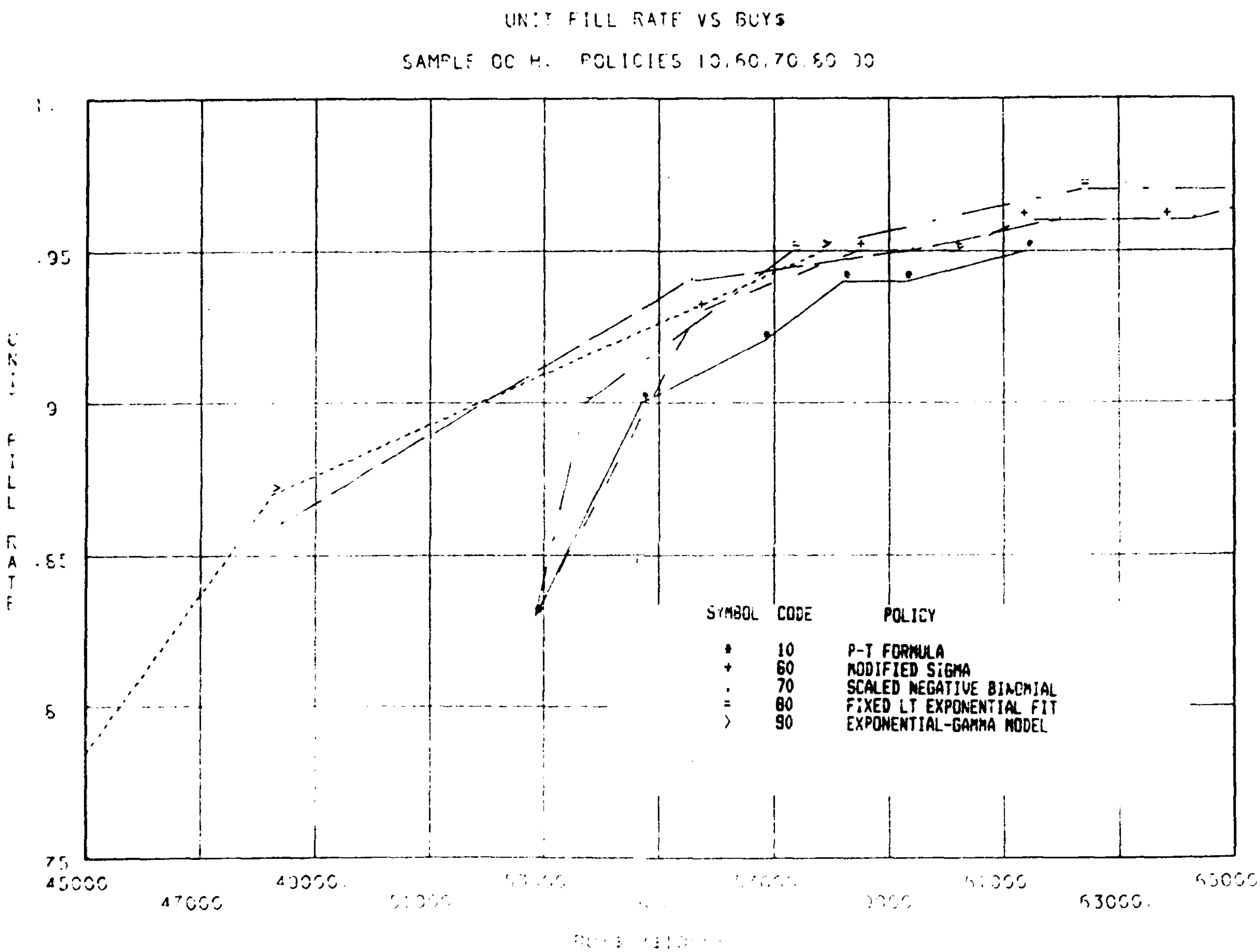
A-2. OC.H Requisition Fill Rate vs Buy Dollars--Close-Up.

#2
C863T
10-6-81



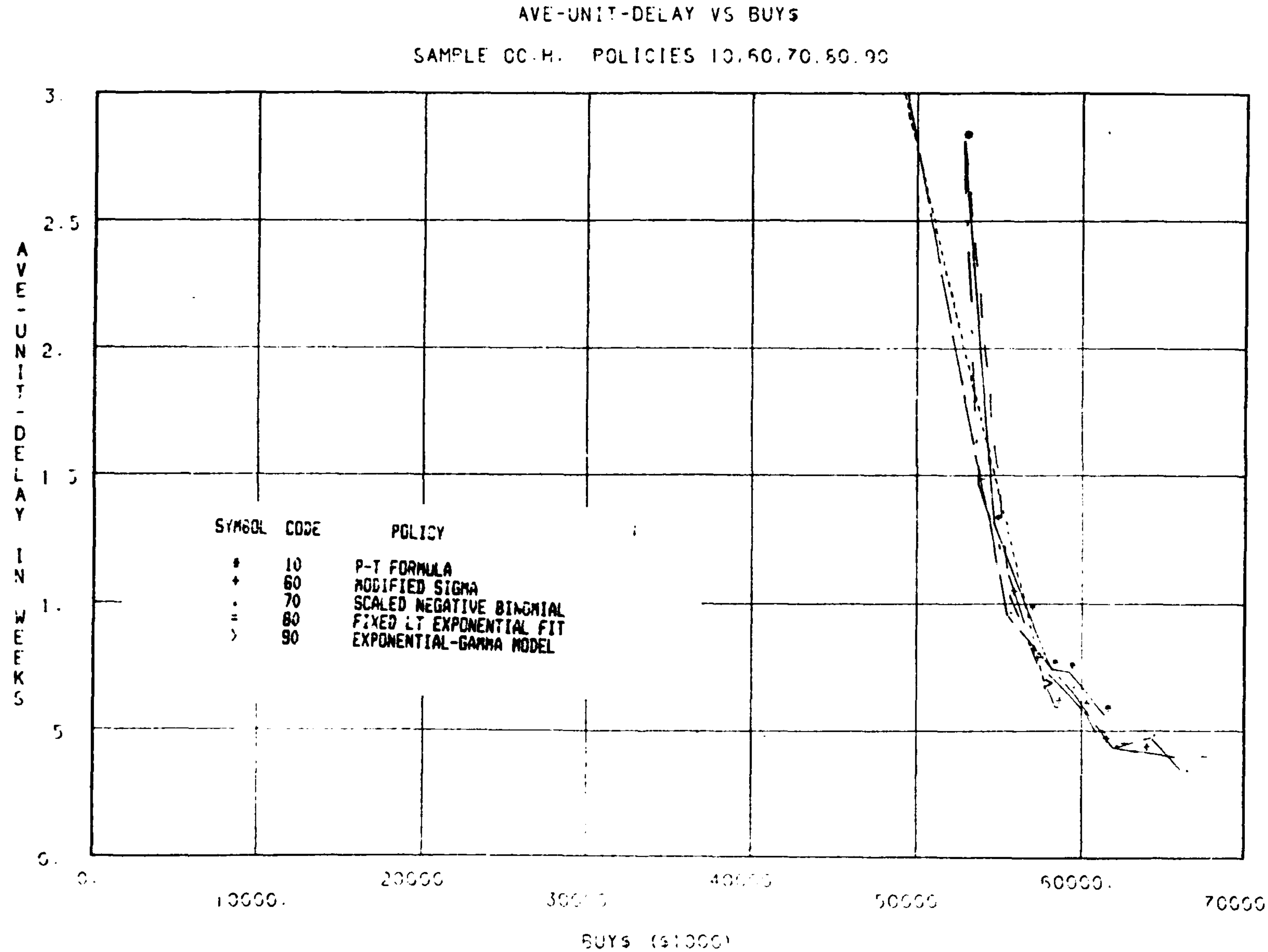
A-3. OC.H Unit Fill Rate vs Buy Dollars.

#3
C863T
10-6-81



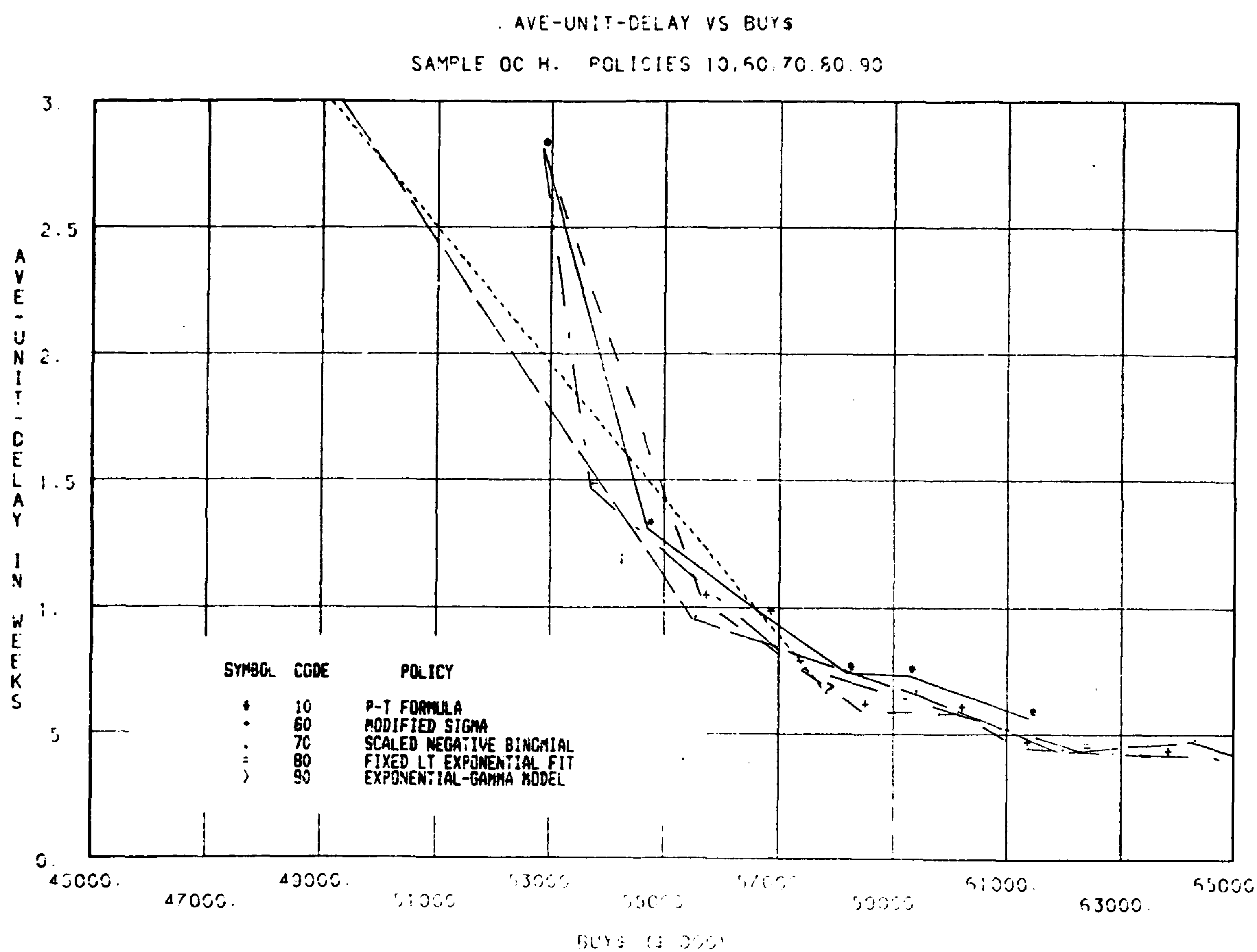
A-4. OC.H Unit Fill Rate vs Buy Dollars--Close-Up.

#H
E863T
0-6-81



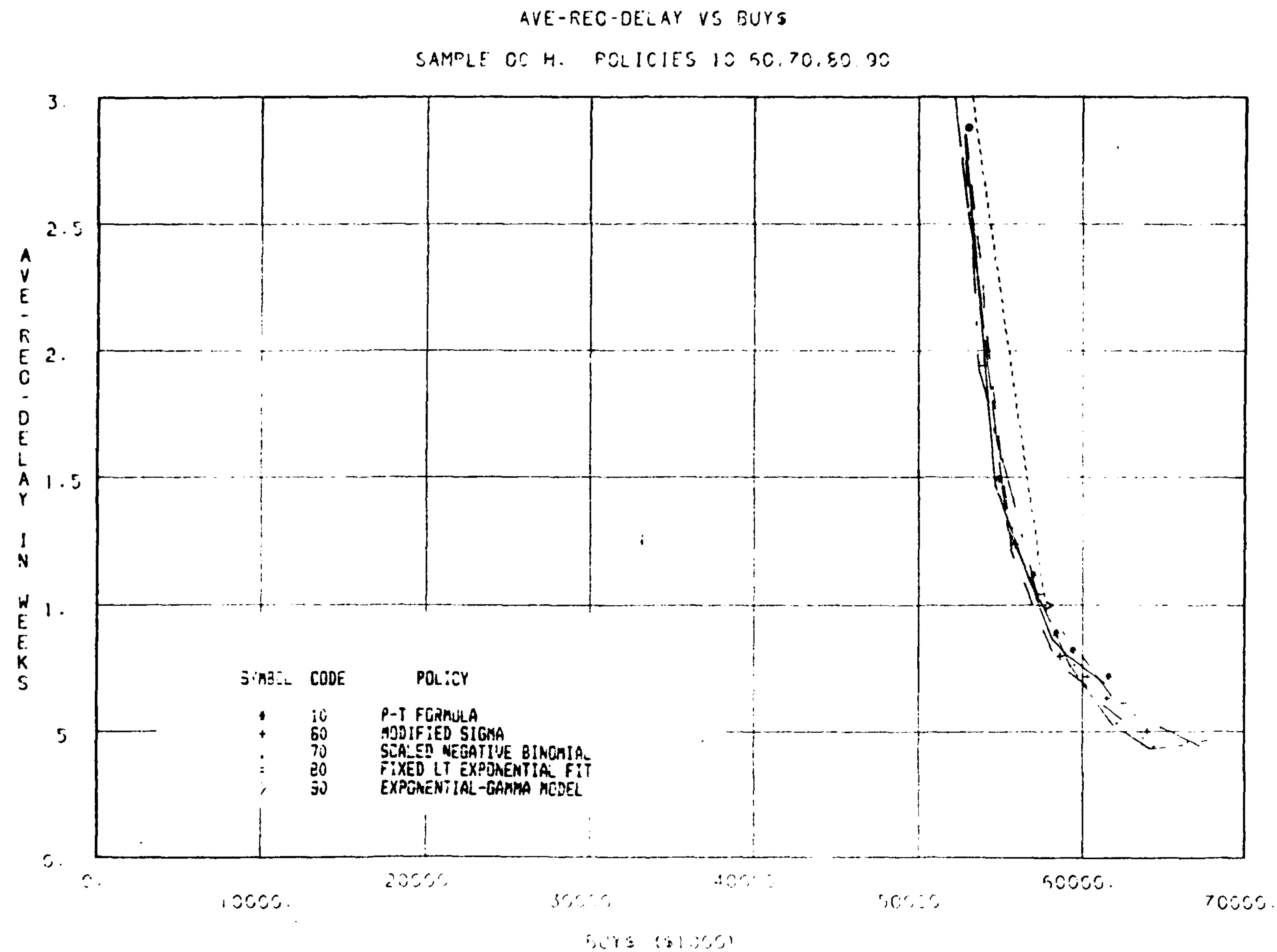
A-5. OC.H Average Unit Delay vs Buy Dollars.

#15
C&57
10-6-81



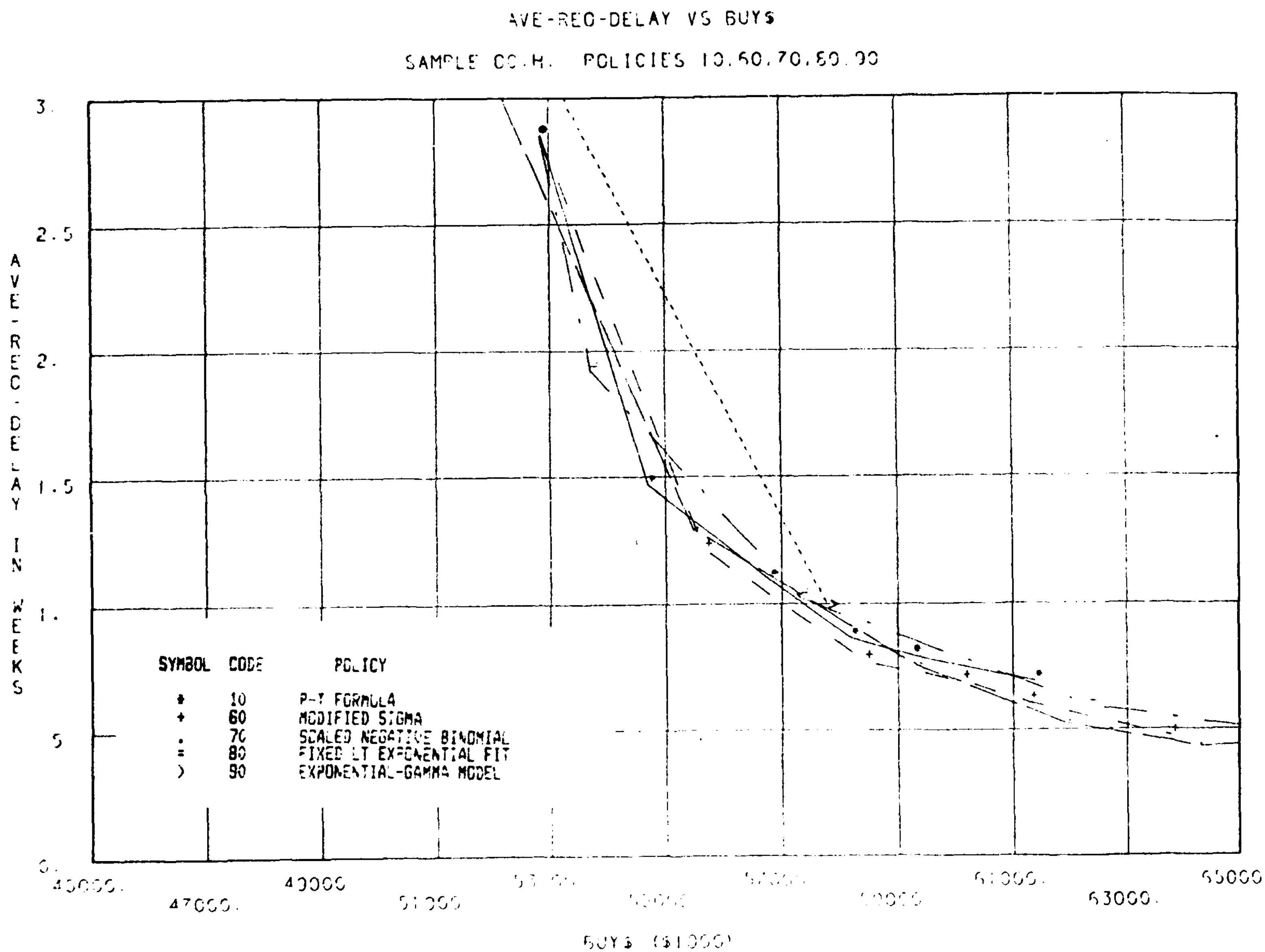
A-6. OC.H Average Unit Delay vs Buy Dollars--Close-Up.

#6
C863T
10-6-81



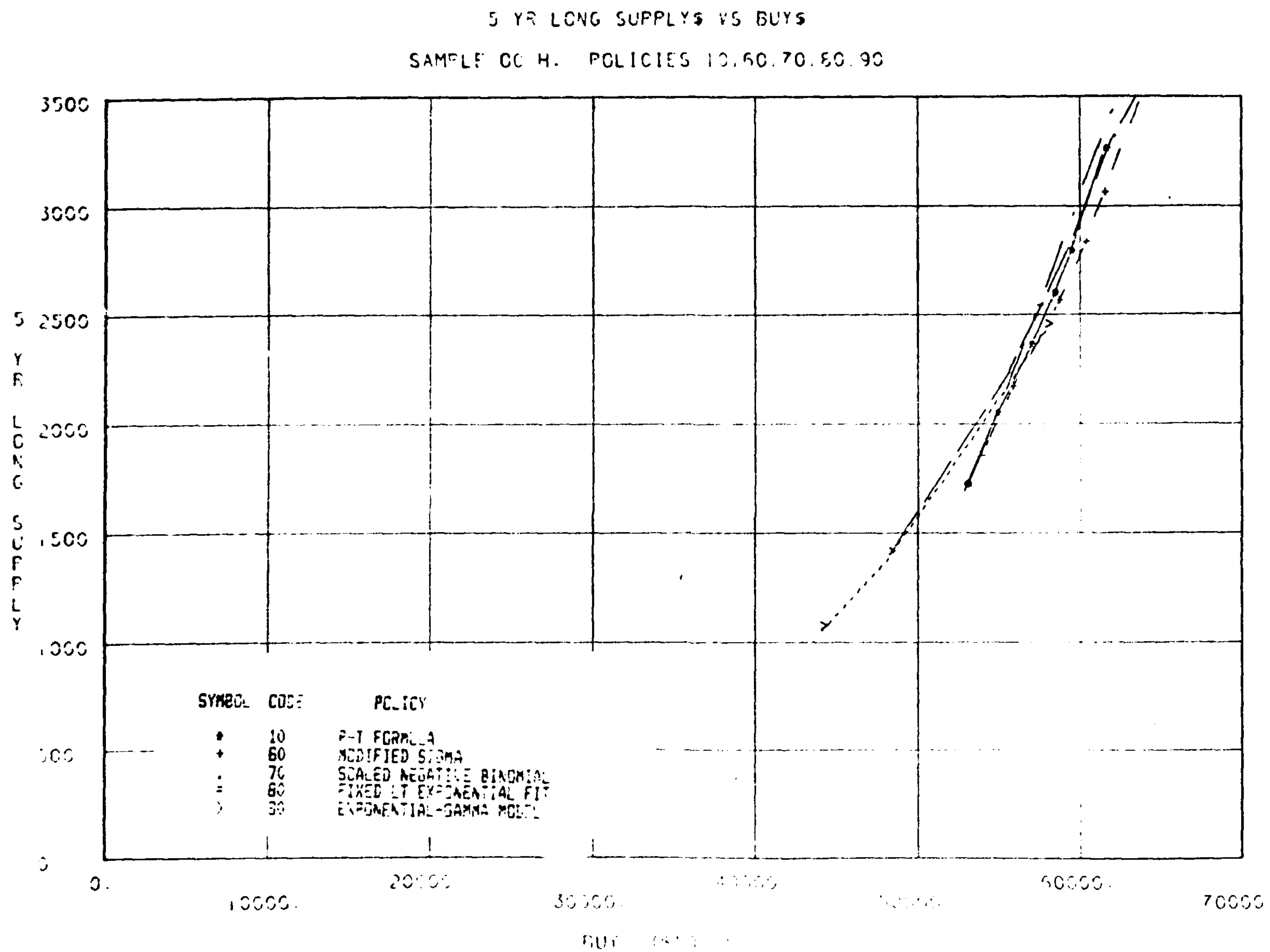
A-7. OC.H Average Requisition Delay vs Buy Dollars.

#7
C 8635
10-6-81



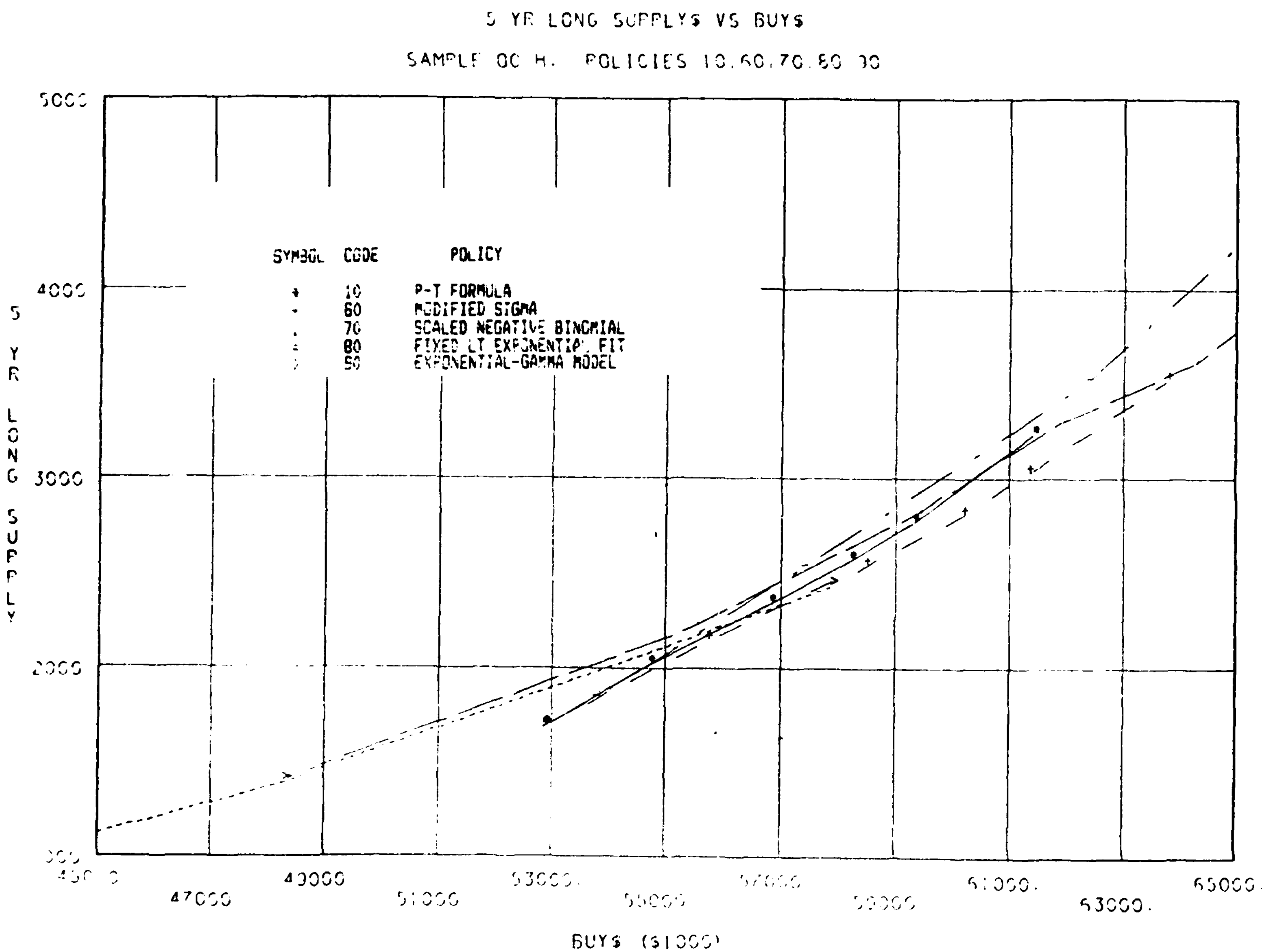
A-8. OC.H Average Requisition Delay vs Buy Dollars--Close-Up.

#8
863T
10-6-81



A-9. OC.H Long Supply vs Buy Dollars.

9
7X5T
1-6-81

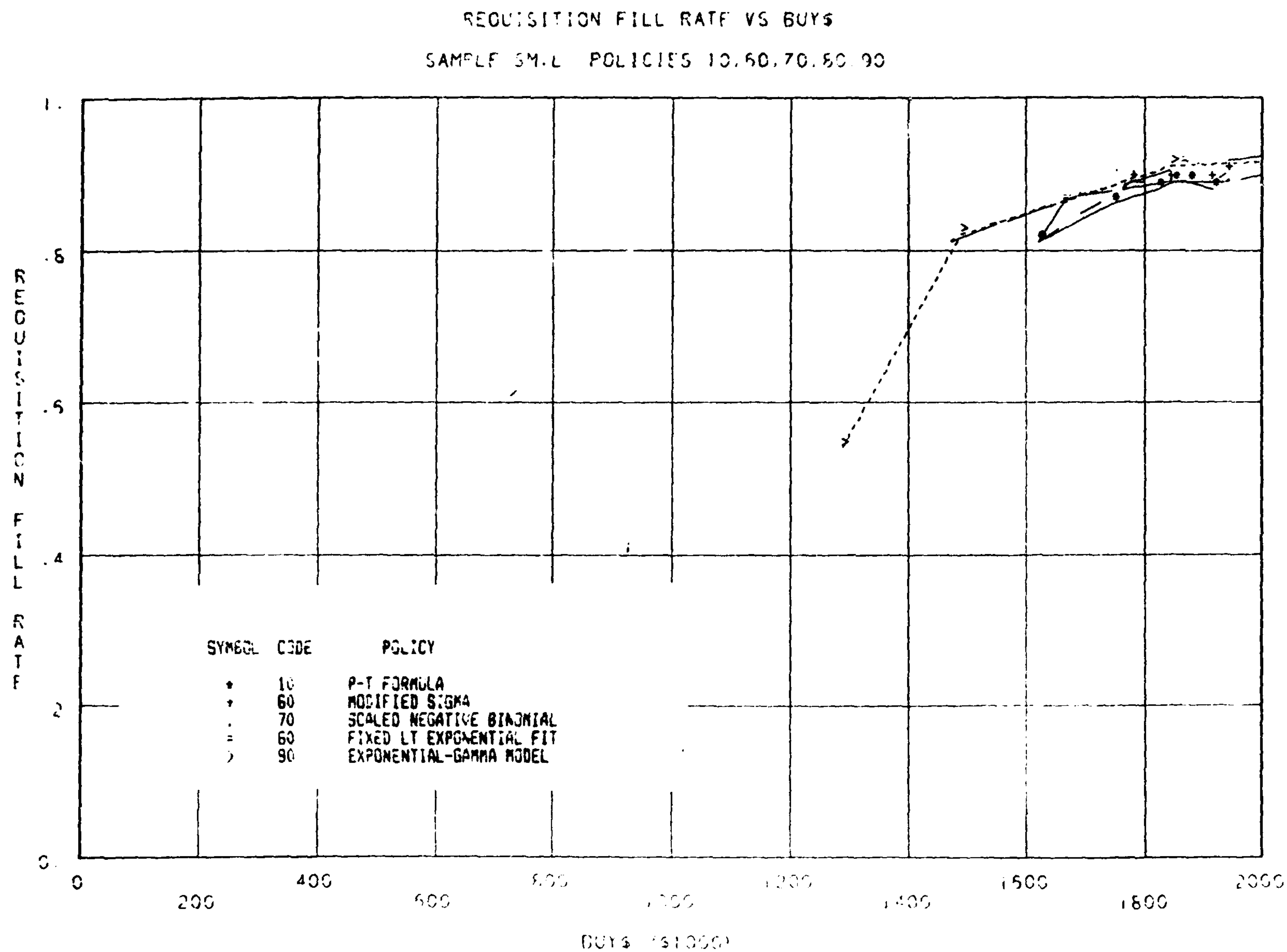


A-10. OC.H Long Supply vs Buy Dollars--Close-Up.

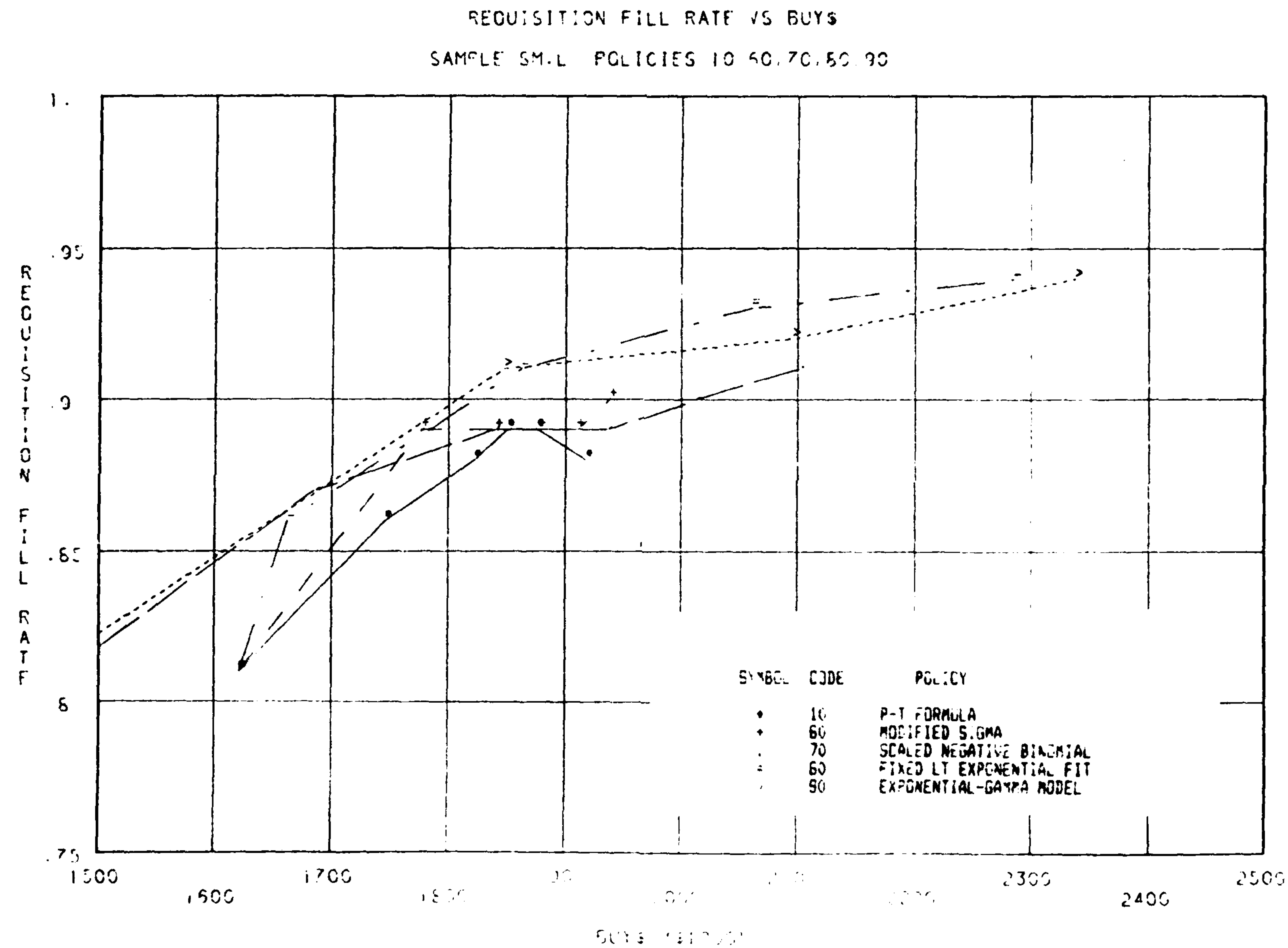
#80
1637
-6-81

Appendix B

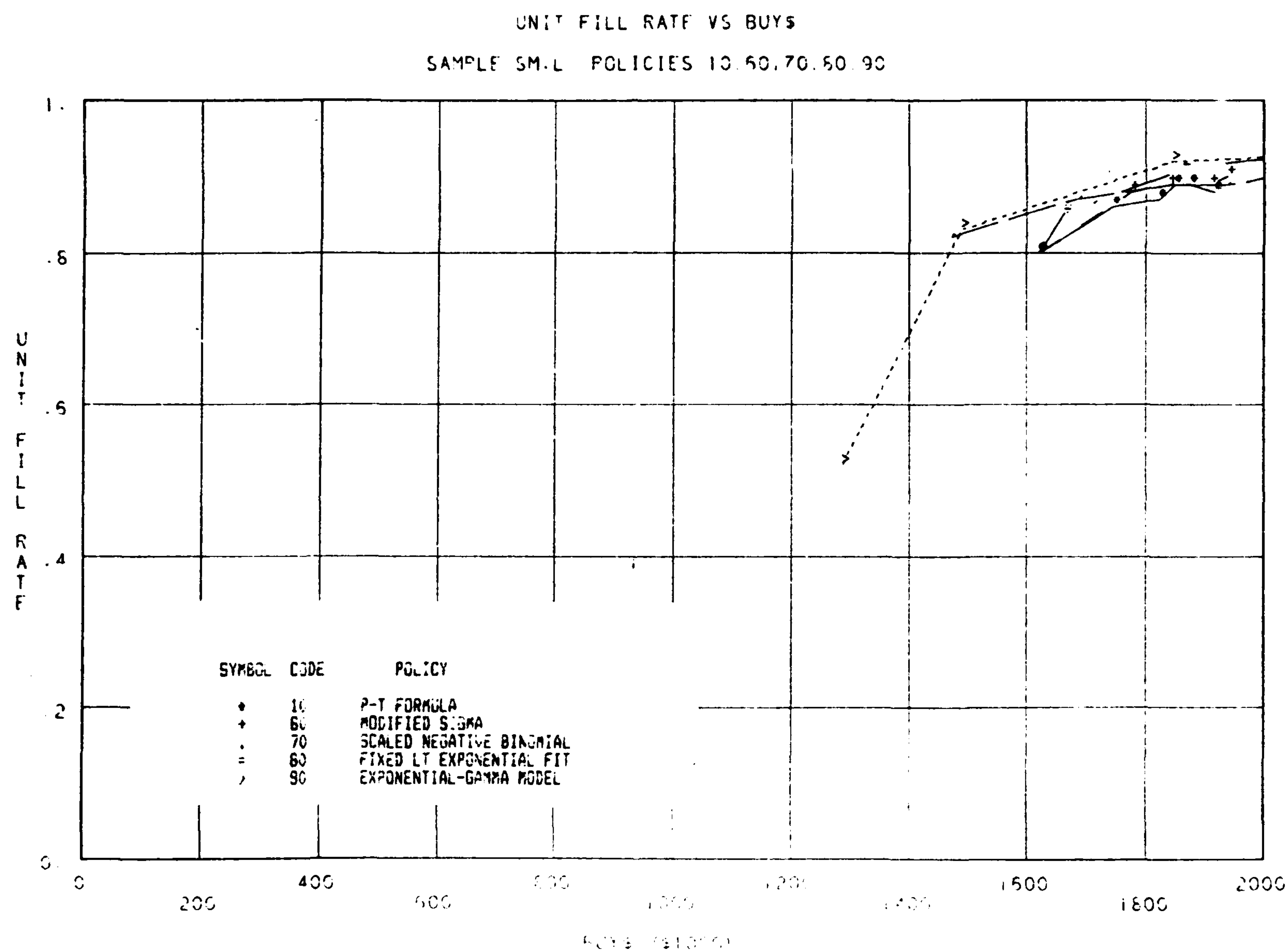
Cost Effectiveness Curves for Sample SM.L



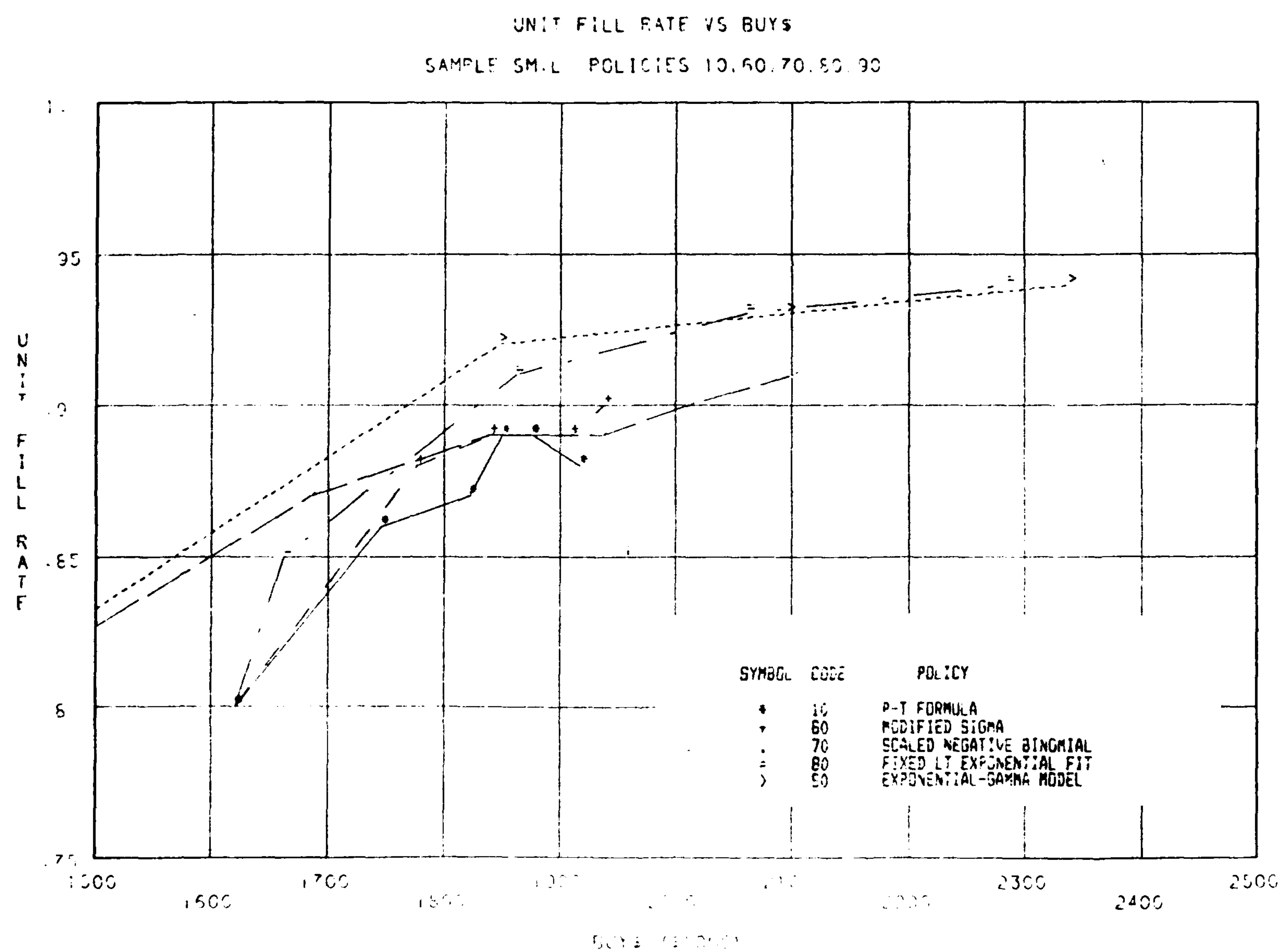
B-1. SM.L Requisition Fill Rate vs Buy Dollars.



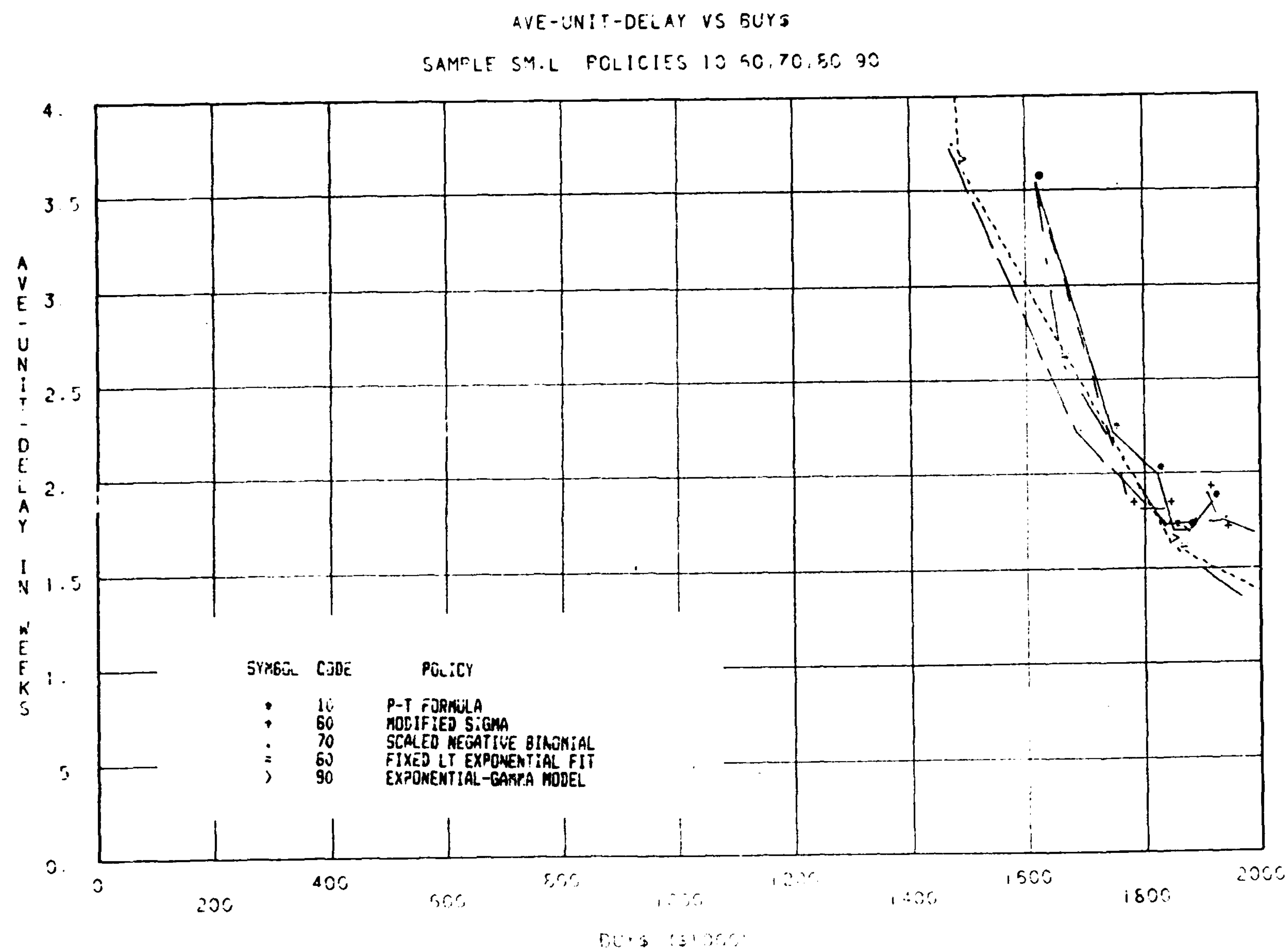
B-2. SM.L Requisition Fill Rate vs Buy Dollars--Close-Up.



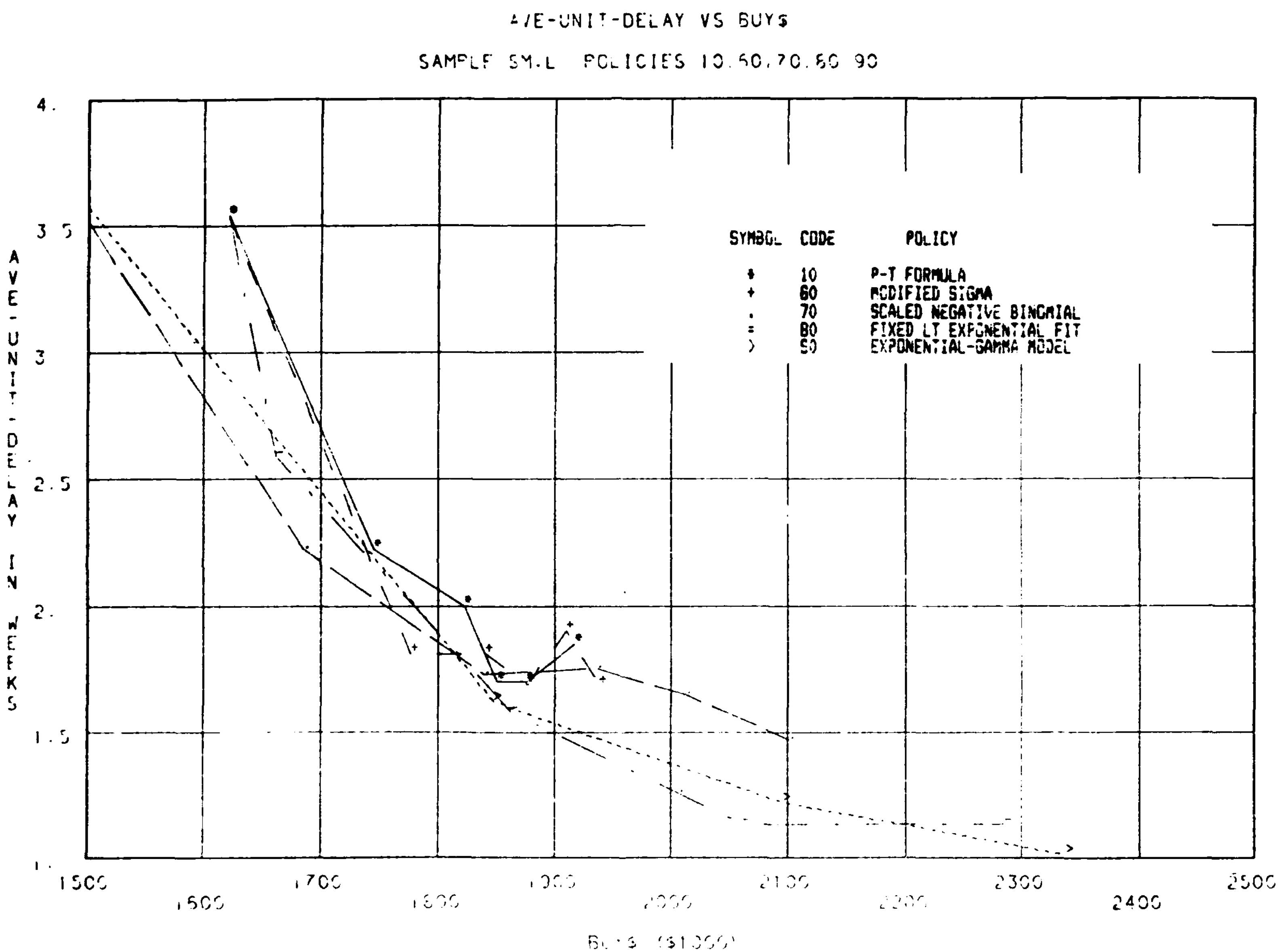
B-3. SM.L Unit Fill Rate vs Buy Dollars.



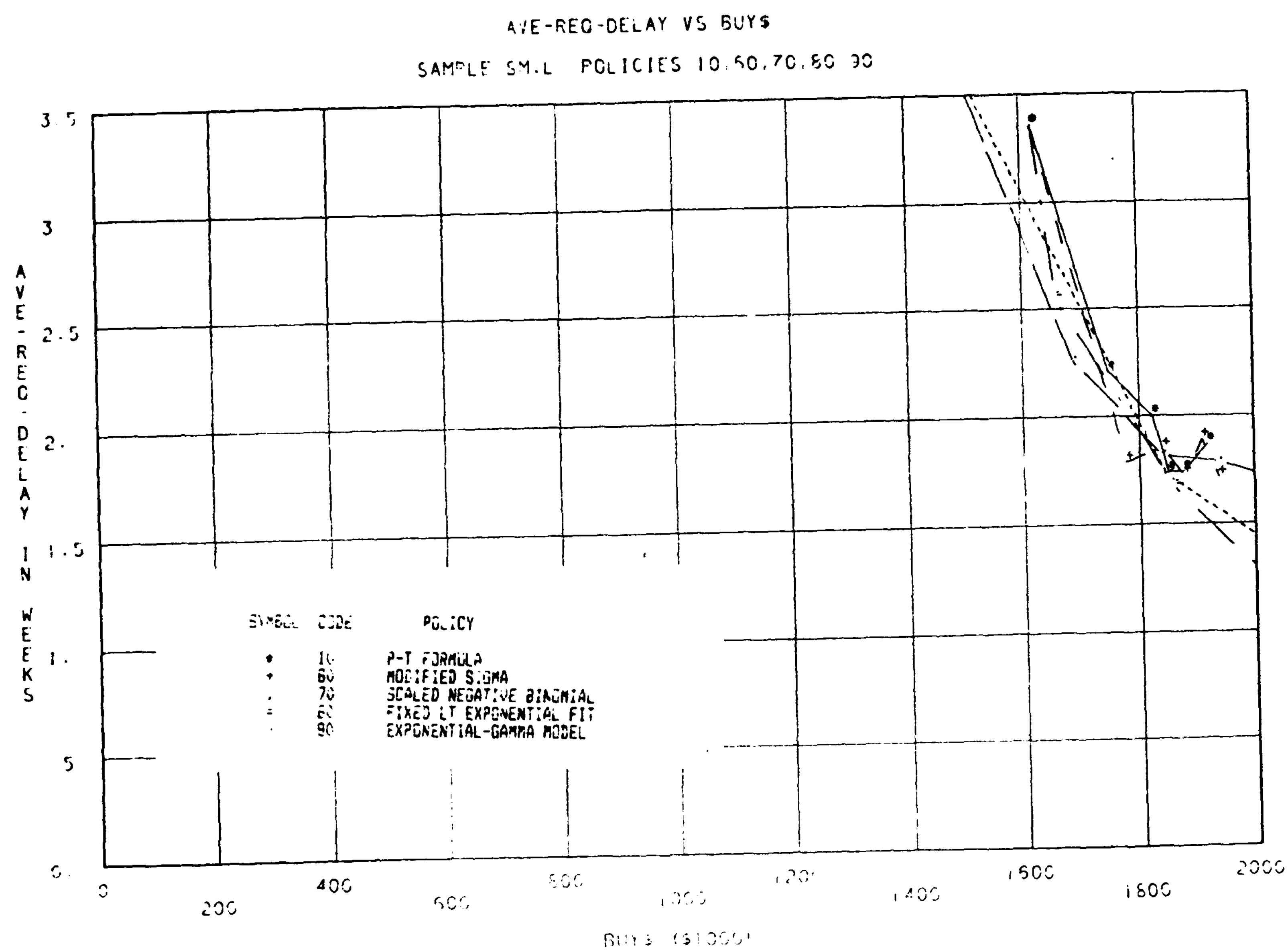
B-4. SM.L Unit Fill Rate vs Buy Dollars--Close-Up.



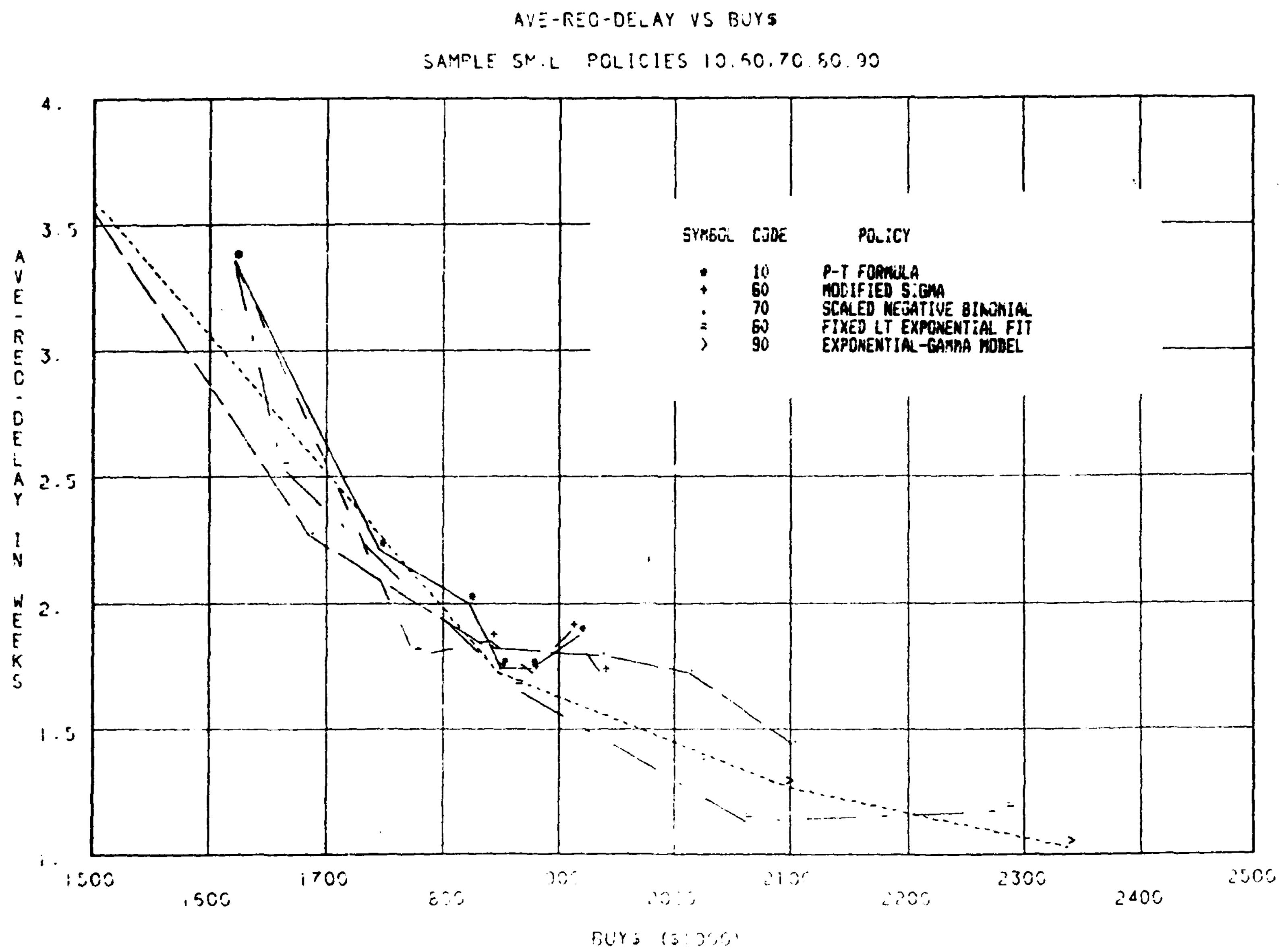
B-5. SM.L Average Unit Delay vs Buy Dollars.



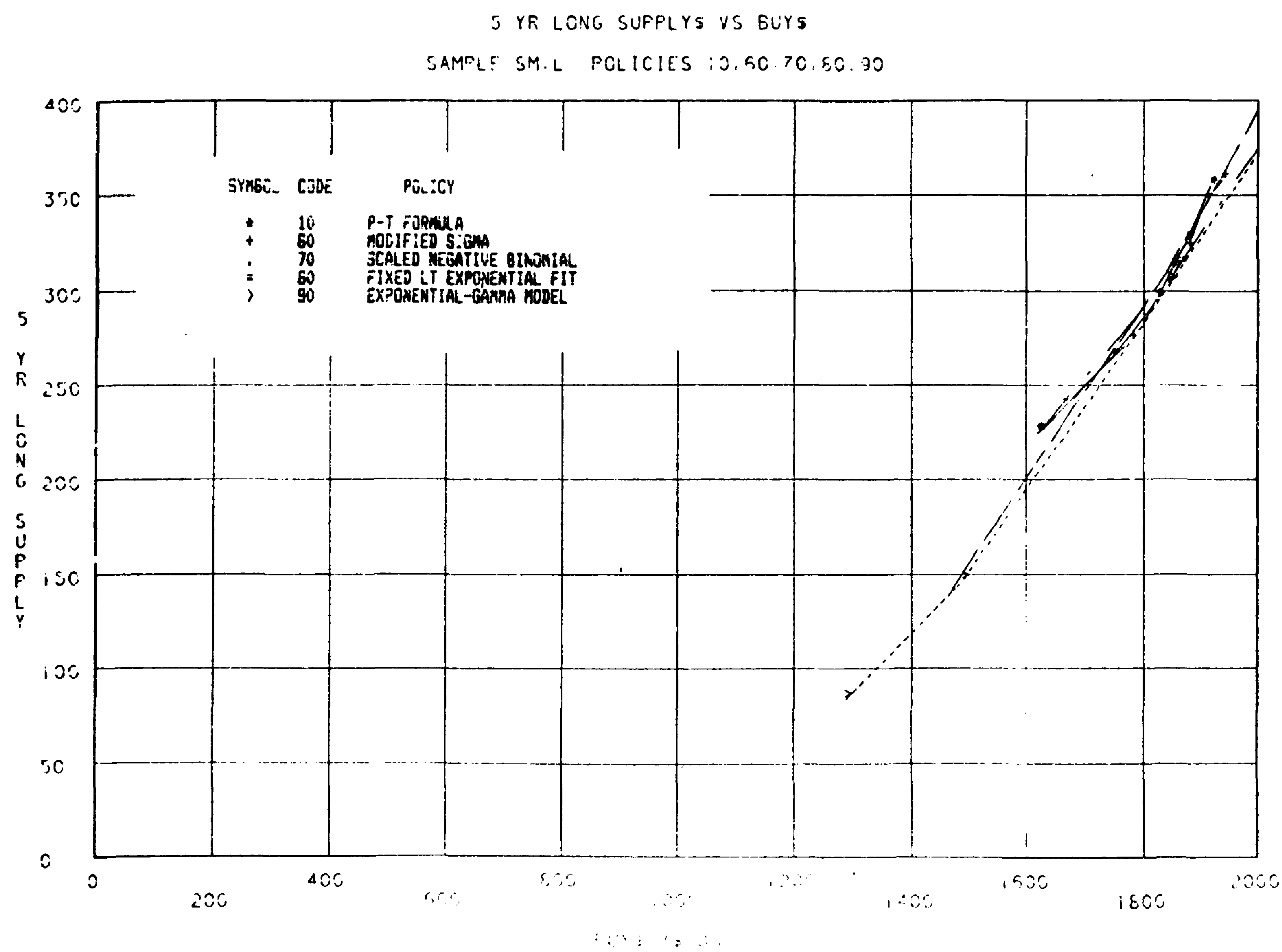
B-6. SM.L Average Unit Delay vs Buy Dollars--Close-Up.



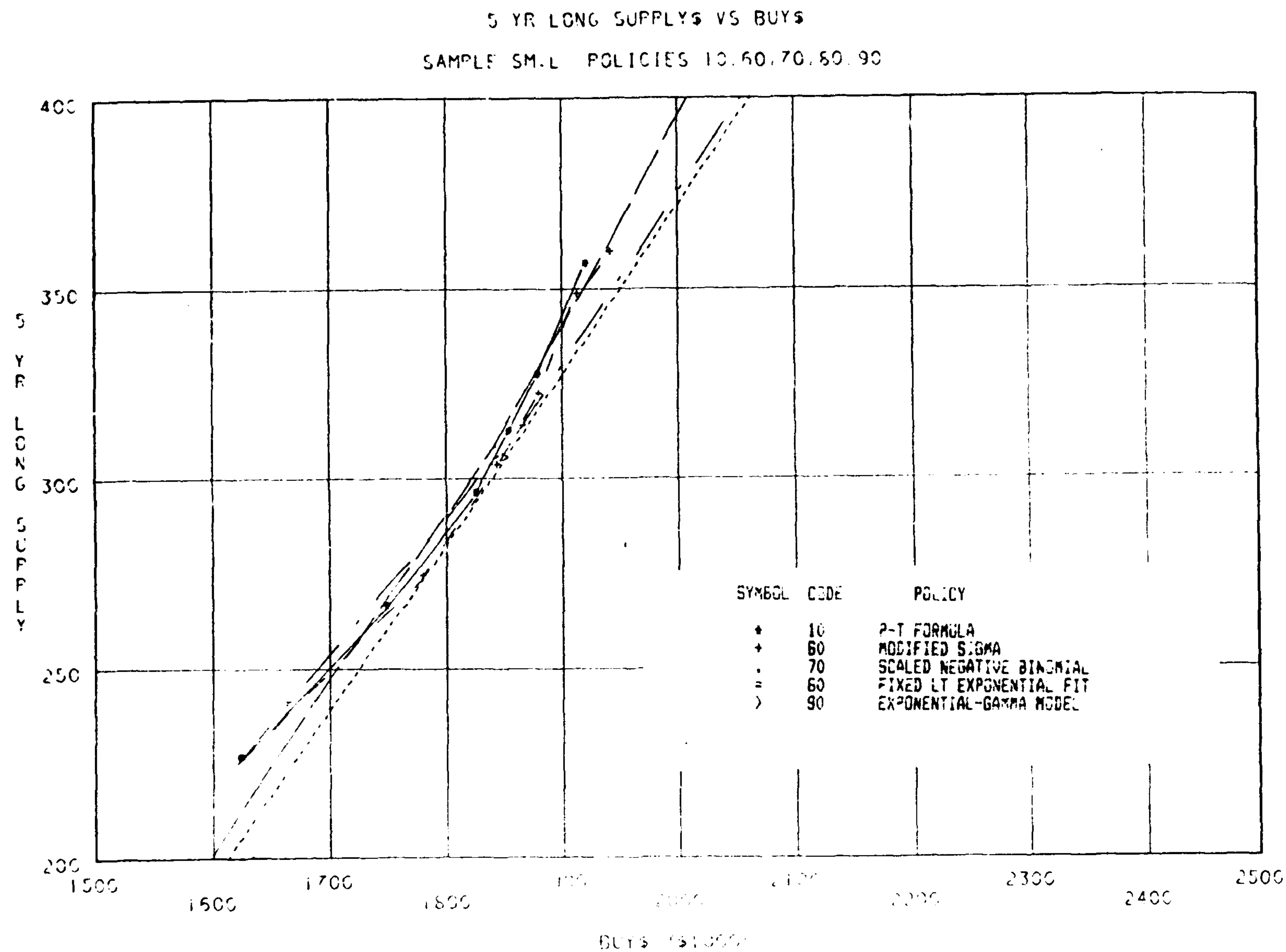
B-7. SM.L Average Requisition Delay vs Buy Dollars.



B-8. SM.L Average Requisition Delay vs Buy Dollars--Close-Up.



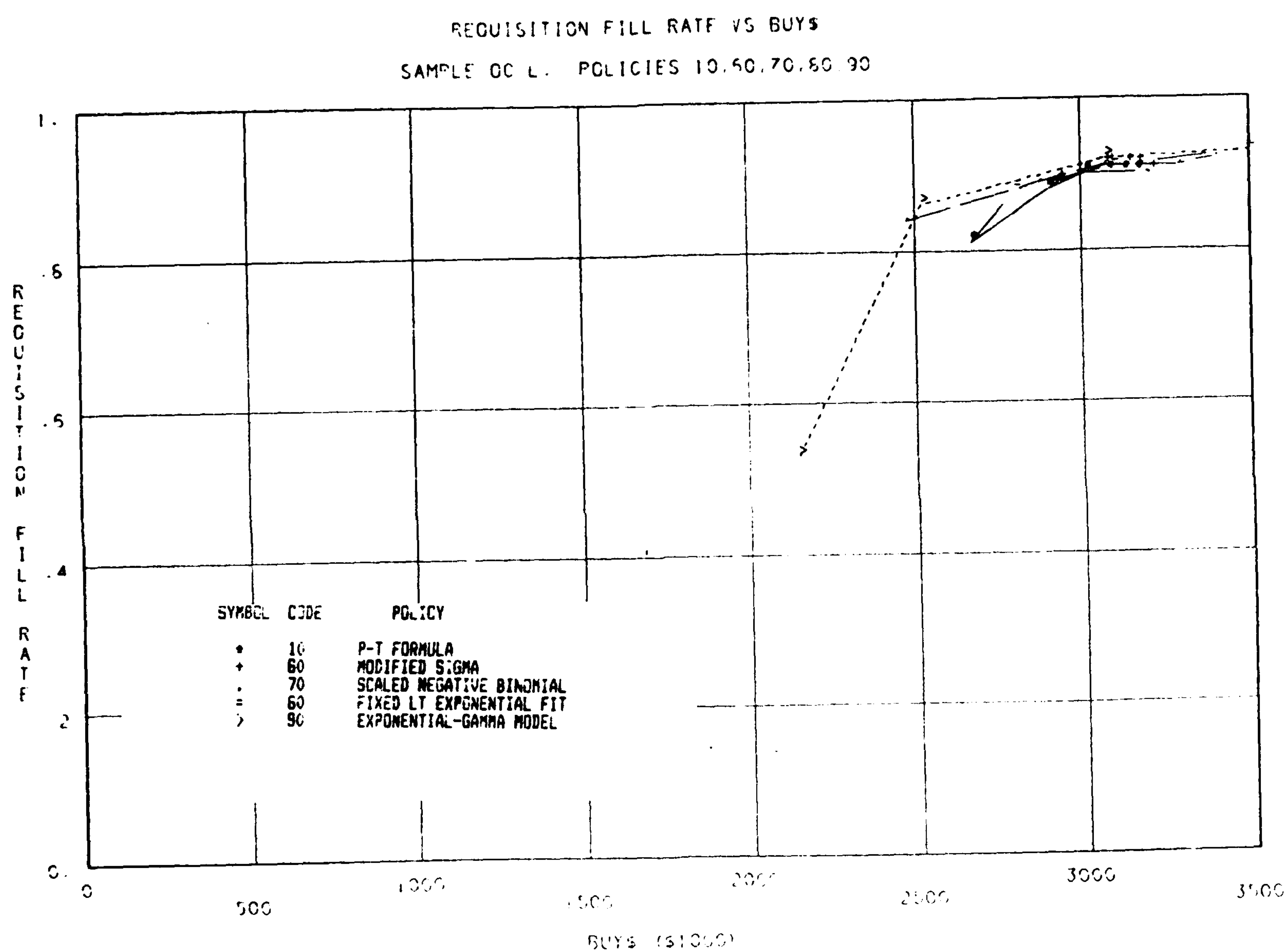
B-9. SM.L Long Supply vs Buy Dollars.



B-10. SM.L Long Supply vs Buy Dollars--Close-Up.

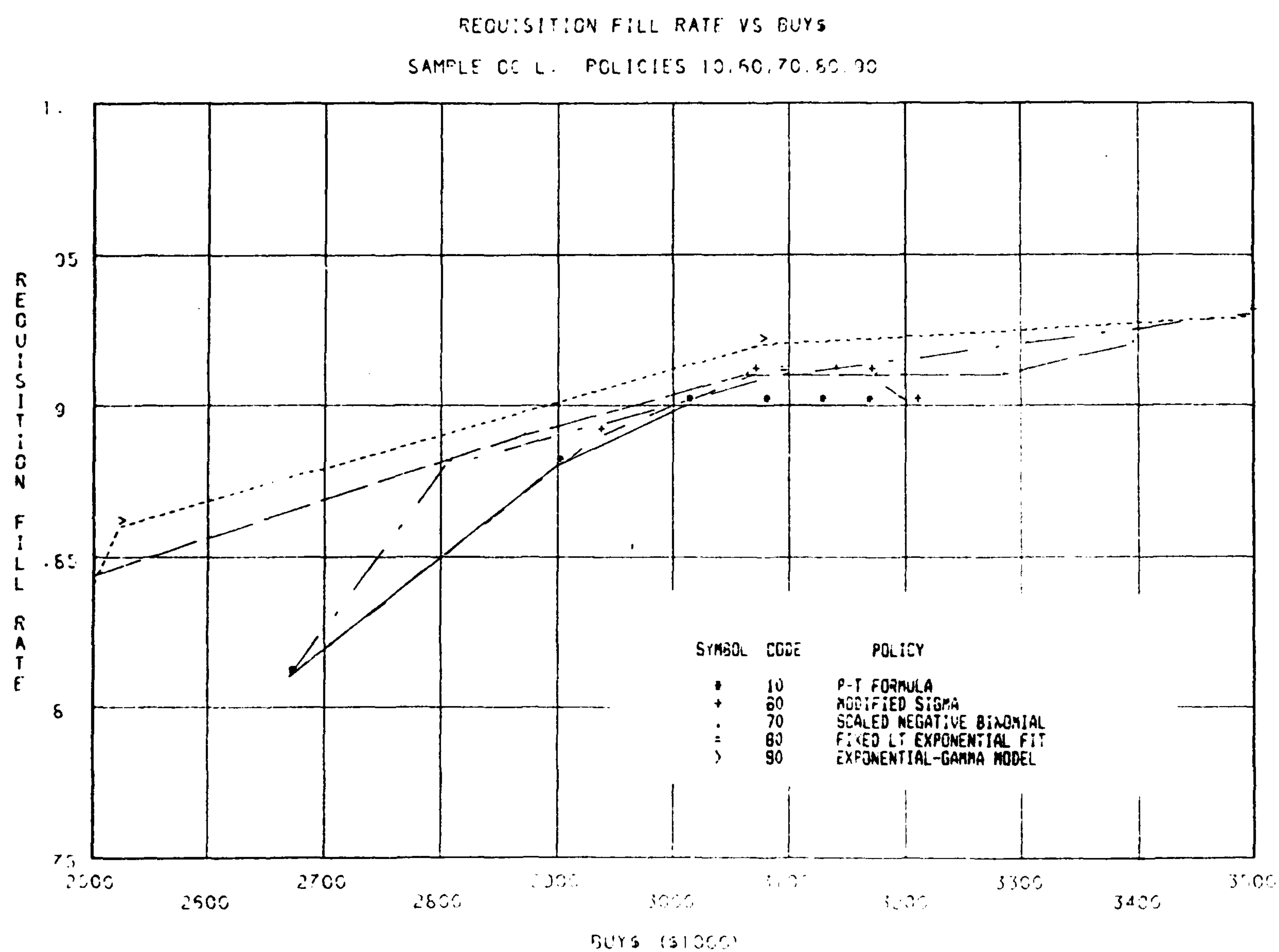
Appendix C

Cost Effectiveness Curves for Sample OC.L



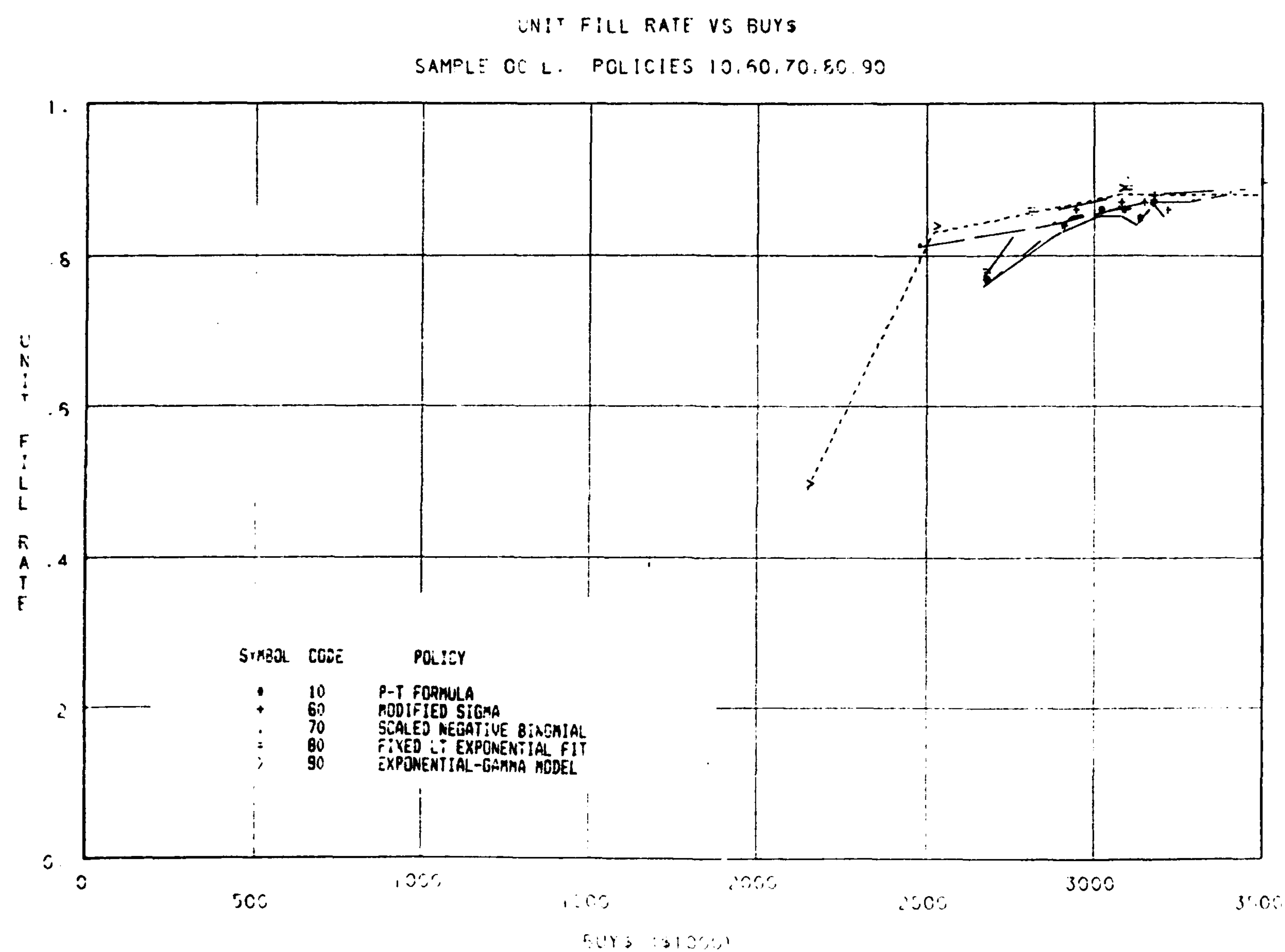
C-1. OC.L Requisition Fill Rate vs Buy Dollars.

2864T
#1
0-6-81



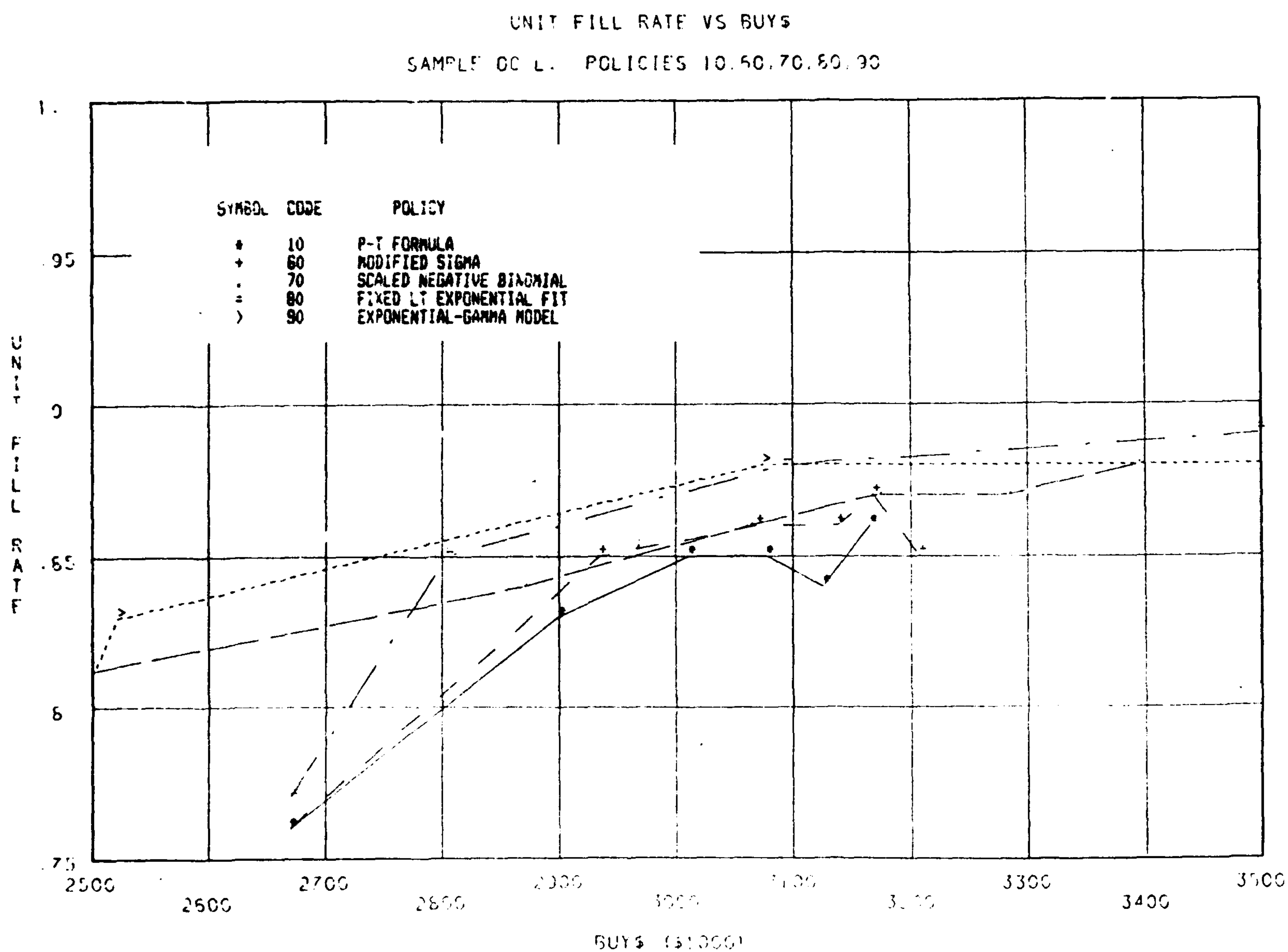
C-2. OC.L Requisition Fill Rate vs Buy Dollars--Close-Up.

C 8L4T
#2
10-6-81

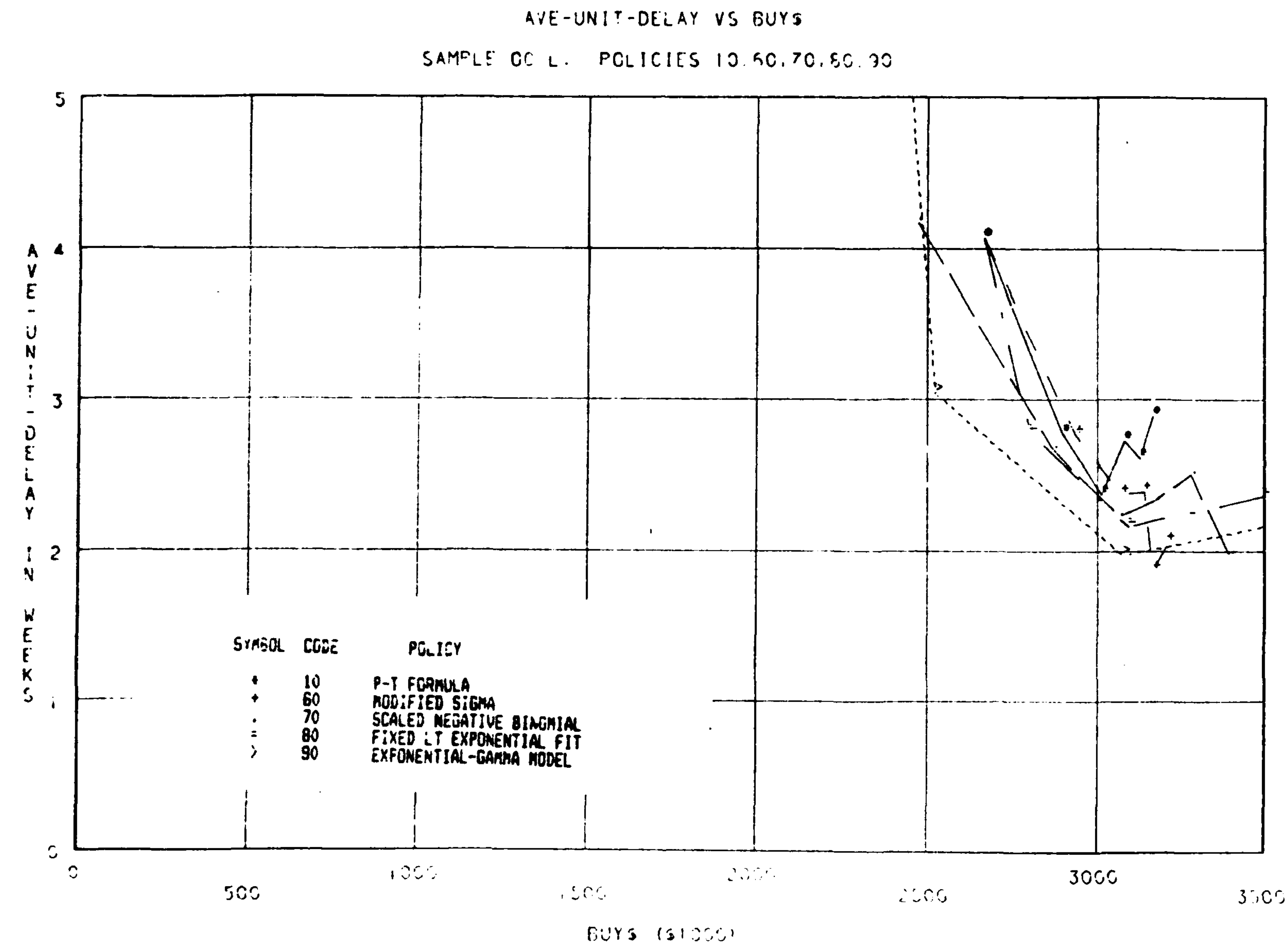


C-3. OC.L Unit Fill Rate vs Buy Dollars.

#3
C864T
10-6-81



C-4. OC.L Unit Fill Rate vs Buy Dollars--Close-Up.

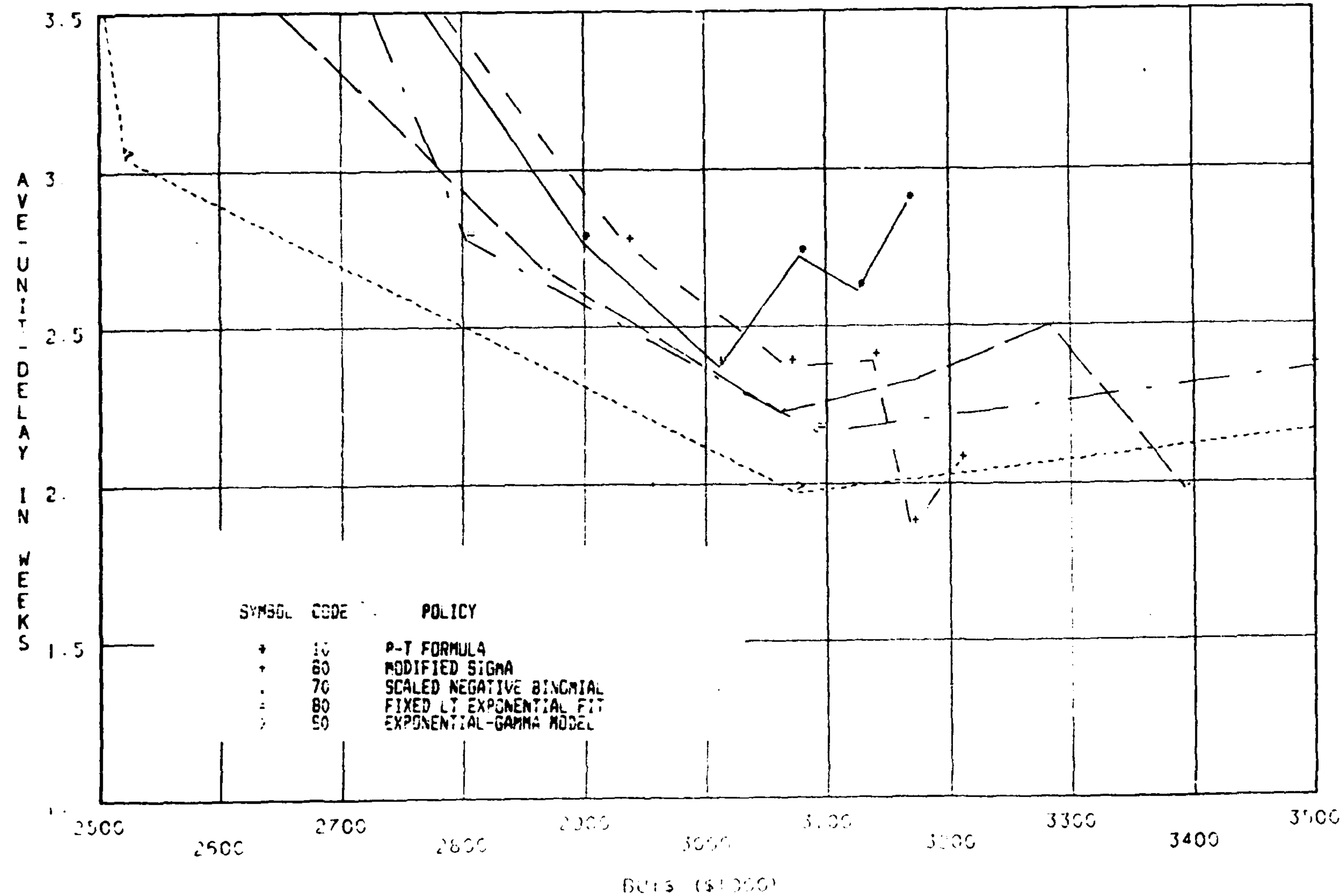


C-5. OC.L Average Unit Delay vs Buy Dollars.

#5
C8645
10-6-81

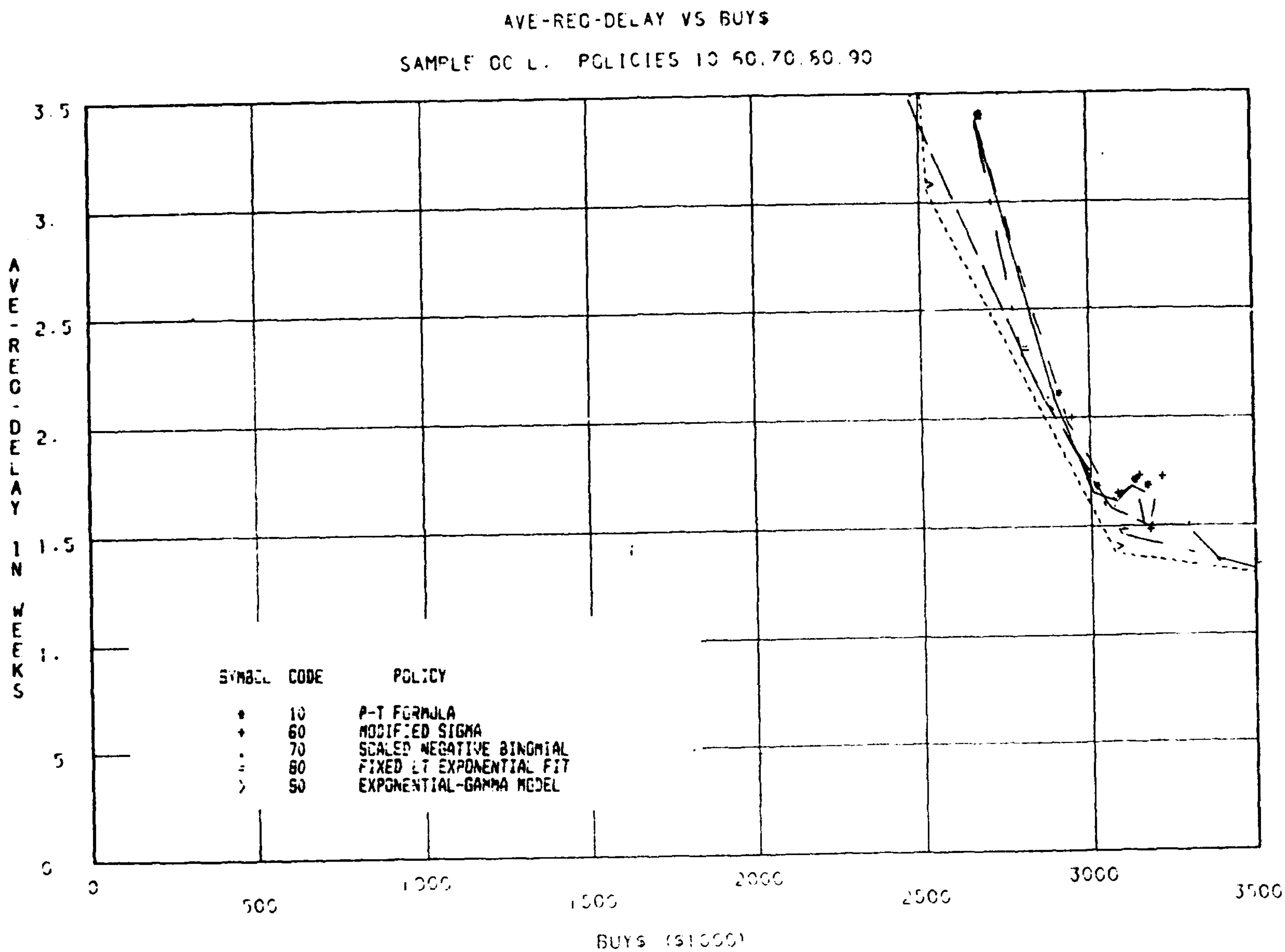
AVE-UNIT-DELAY VS BUYS

SAMPLE OC.L. POLICIES 10,60,70,80,90



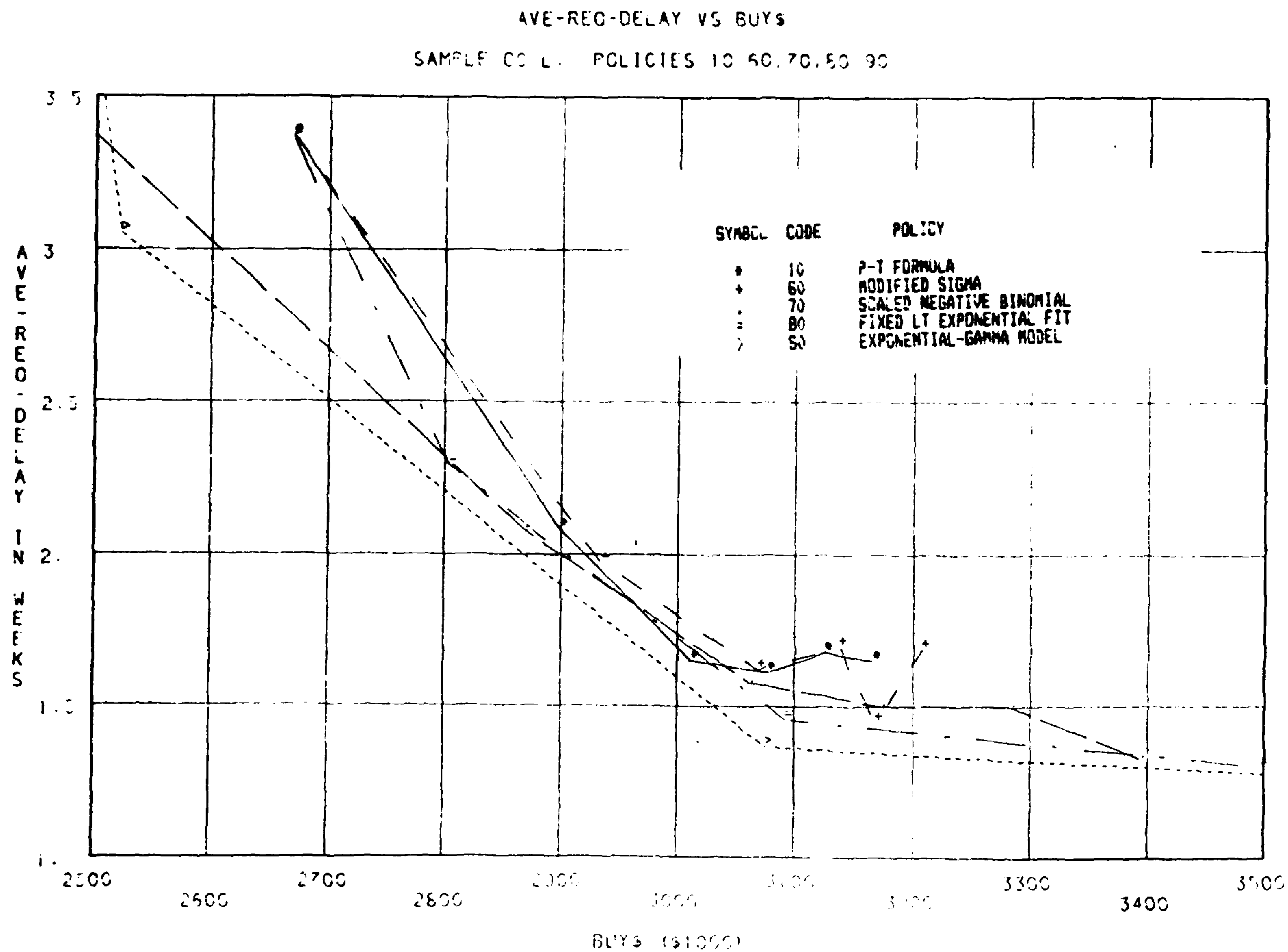
C-6. OC.L Average Unit Delay vs Buy Dollars--Close-Up.

#6
C864T
D-6-81

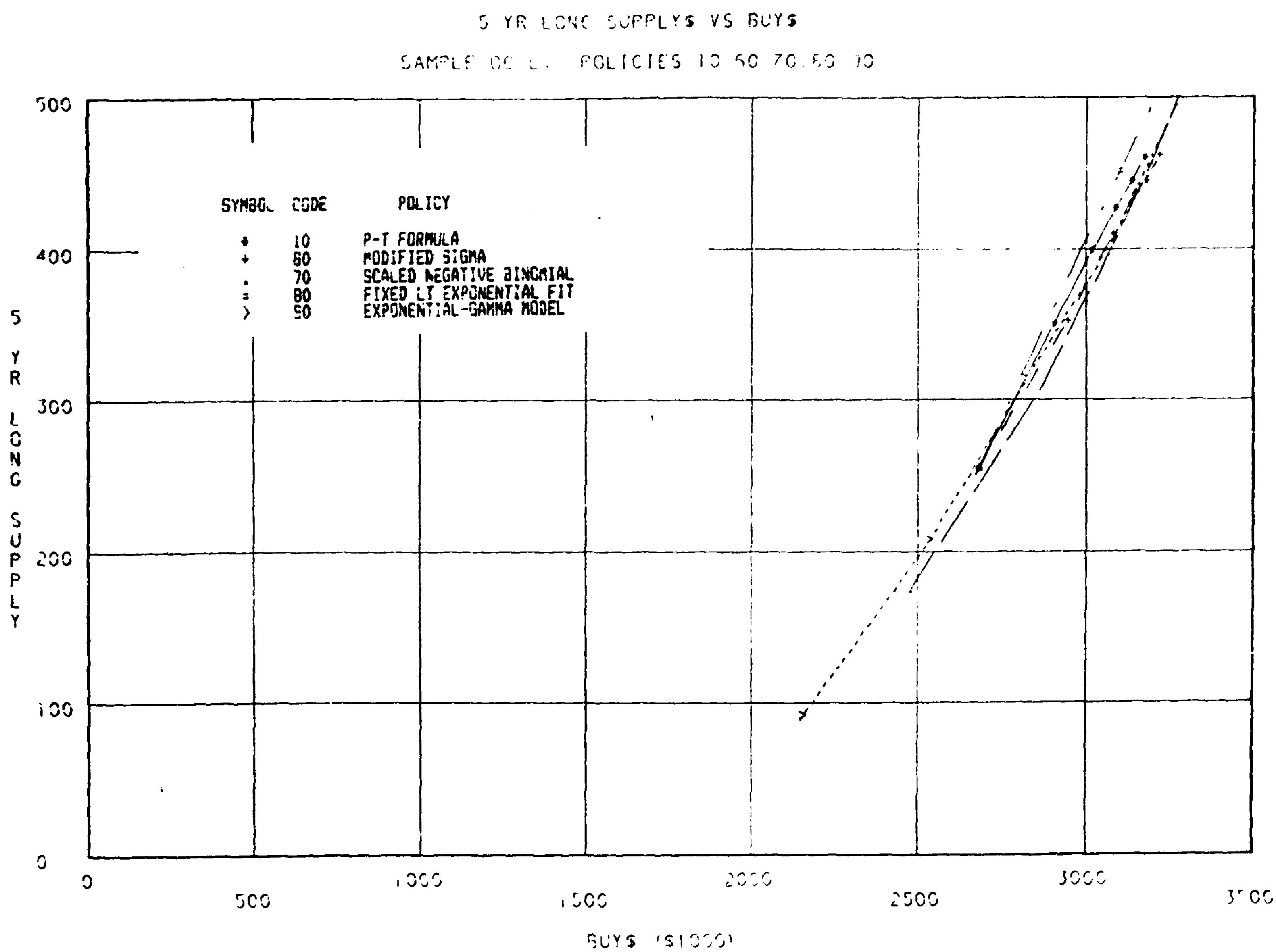


C-7. OC.L Average Requisition Delay vs Buy Dollars.

#7
C847
0-6-81

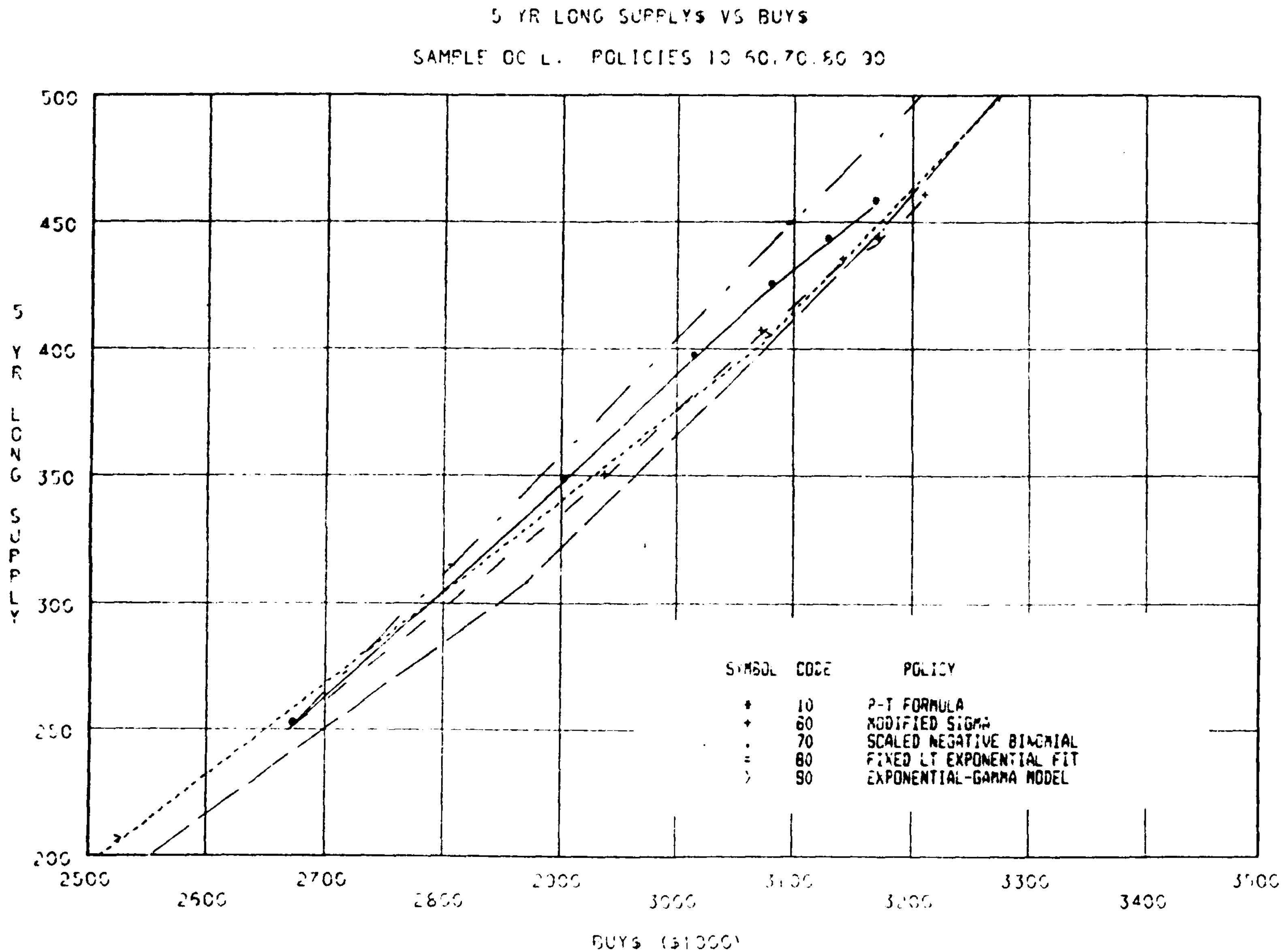


C-8. OC.L Average Requisition Delay vs Buy Dollars--Close-Up.



C-9. OC.L Long Supply vs Buy Dollars.

#9
C624T



C-10. OC.L Long Supply vs Buy Dollars--Close-Up.

E

ED